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THE DEPLOYMENT OF DIGITAL HR TECHNOLOGIES AS A TOOL FOR ENHANCING ENTERPRISE PRODUCTIVITY IN THE DIGITAL ECONOMY

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ABSTRACT

Relevance of the study

The relevance of this study stems from the imperative to integrate HRTech solutions to enhance productivity within the digital economy, signifying a paradigm shift in human capital management, and the necessity to institutionalize Employer Branding as a driver for sustainable development.

Purpose of the study

The study aims at formalizing a hybrid HRTech Framework integrated with Employer Branding, alongside verifying its impact on labor productivity through econometric modeling, cognitive-emotional stratification, as well as architectural interoperability.

Research methods

The methodologies employed in this research include SWOT analysis, econometric modeling, structural synthesis frameworks, cognitive-emotional modeling, and econometric validation.

Results obtained

The integrative analysis revealed the superior efficacy of People Analytics (0.84; ΔLP +18.2%; fluctuation –25.3%), AI communications (0.82; TTTHR –21.4%; inclusivity +15.9%), and HRIS (0.80; HRΔCOE –23.1%; adaptability +39.6%). Based on these findings, a tri-layered HRTech Framework incorporating Employer Branding architecture was devised, which facilitates cognitive traceability and brand extrapolation. Upon validating the project framework, a noteworthy enhancement in key performance indicators was documented (ΔLP +19%, TTTHR –24%, RRI = 0.84, AIU = 0.88, EER = 0.86), indicating a high degree of cognitive relevance, HR conversion efficiency, and digital adaptability of the model within the context of strategic HR digitalization.

Scientific novelty of the study

The scientific novelty of this study lies in formalizing the HRTech Framework with Employer Branding as a hybrid architecture that synergizes People Analytics, AI communications, and HCM solutions with brand-oriented modules, thereby providing cognitive traceability, integrative influence, and affective validity in the context of digital productivity.

Prospects for future research

The prospects for future research entail comprehensive implementation of the HRTech Framework with Employer Branding in a tangible HR environment, concentrating on behavioral dynamics, institutional interoperability, and brand-oriented adaptation. It is advisable to initiate a controlled pilot project with traced verification of procedural resilience, AIU stability, as well as the framework's digital efficacy.

Keywords: *Employment, Labour, Wage, Economic Empowerment, Smes, Sustainable Development, Green Job*

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1. INTRODUCTION

The conditions of the post-pandemic economy reorganization, the growth of cognitive demands on employees, as well as digital infrastructure evolution have engendered a profound transformation in terms of the conceptual underpinnings within human resource management. The digitalization of business processes necessitates that HR practitioners not only adapt technologically but also strategically recalibrate their focus towards cultivating a cognitively resilient environment. The establishment of dynamic capacity amid digital flexibility and instability can only be achieved through a comprehensive competencies reassessment, structural roles, and interactions within the service sector [1]. At the same time, the institutionalization of Smart HR within the digital ecosystem of public administration presents new challenges for both state and corporate HR policies [2]. Furthermore, there is a growing trend towards a humanitarian reinterpretation of HR frameworks, emphasizing value orientation, empathic infrastructure, and employees' cognitive-emotional engagement. It is of note that the significance of education-centric and human-centered approaches in fostering sustainable capacity in public administration is increasingly recognized [3]. These dimensions underscore the imperative to integrate cognitive-emotional models into HRTech solutions and to investigate their influence on productivity, particularly within the paradigms of Employer Branding and Well-being.

The purpose of this study is the design and formalization of a hybrid HRTech Framework incorporating Employer Branding, alongside an examination of its integrative impact on productivity through the application of econometric modeling, cognitive-emotional stratification, and architectural interoperability.

Research hypothesis. The integration of cognitive-analytical HRTech solutions (People Analytics, AI-driven communication, HRIS/HCM) within a tri-layered HRTech Framework with Employer Branding generates a significant integrative enhancement of labor productivity, driven by cognitive traceability, semantic interoperability, and affective-engagement actualization across key HR performance indicators.

Research objectives:

- Conduct a strategic stratification of HRTech solutions employing SWOT analysis to discern high-performance digital technologies.
- Carry out econometric modeling to assess the integrative impact of HRTech on labor productivity indicators.
- Develop the structural architectonics of the HRTech Framework with Employer Branding, concentrating on the bidirectional impact of Employer Branding
- Implement cognitive-emotional modeling to evaluate the actualization of Employee Value Proposition (EVP) and affective engagement.
- Undertake econometric validation of the framework based on criteria of integral impact on Labor Productivity (LP), Employee Engagement Rate (EER), Affective Interaction Utility (AIU), and HR efficiency.

2. LITERATURE REVIEW

The literature review was necessitated by the imperative to systematize scientific findings regarding the influence of digital HR technologies on labor productivity and organizational efficacy within the framework of the digital economy. This review facilitated the identification of key technological drivers, methodological paradigms, and impediments to implementation, which formed the foundation for subsequent research.

In this context, the authors [4] established that digital technologies and HR practices exhibit a profound conceptual interdependence, thereby constituting the bedrock of competitive advantages in the digital economy. At the same time, methodological limitations inherent in the systematic review were discerned, constraining the potential for extrapolation to empirical scenarios.

Against this backdrop, the researcher [5] found a lack of statistically significant impact of digital learning, flexible employment modalities, and fundamental HR digitalization on productivity ($p > 0.05$). Conversely, the positive correlation between innovative recruitment practices and AI-driven HR analytics with respect to productivity and organizational effectiveness was substantiated ($p = 0.000$).

Delving into the above findings, the authors [6] demonstrated that the integration of Big Data, AI, and blockchain catalyzed enhancements in HRM efficiency and the overall quality of the work experience. Concurrently, information security risks, transformative challenges to management paradigms, as well as deficiency in personnel competencies were identified.

Elaborating on the technological solutions impact, the scientist [7] established that the implementation of AI, Big Data, cloud-based HR systems, and automation precipitated a remarkable increase in HR efficiency (+40%), job satisfaction (+66%), and employee engagement (+31%). Nonetheless, barriers to digital transformation, manifested as organizational resistance, a lack of requisite competencies, financial constraints were also recognized.

In the field of sustainable practices, the researchers [8] evidenced that the digital maturity of HR significantly enhanced the capability to cultivate and retain green talent within a sustainable supply chain. Apart from that, institutional and technological disparities characteristic of small and medium-sized enterprises (SMEs) were identified.

From the startup ecosystem perspective, the author [9] elucidated that HRTech startups, by integrating AI and data analytics, have revolutionized talent management into adaptive, inclusive, and data-driven frameworks. Their influence on increasing analytical effectiveness, organizational readiness, and cognitive elasticity within work environments was substantiated.

Regarding smart workspaces, the researchers [10] discovered that the deployment of HR digital tools through cloud systems, communication platforms, and productivity assessment instruments fostered the growth of employee engagement and satisfaction. However, barriers to transformation, including organizational readiness, resistance to change, and the necessity for continuous learning, were also acknowledged.

Further exploring this issue, the authors [11] revealed that the integration of AI and digital HR technologies has intensified operational efficiency, algorithmic optimization, and the reduction of recruitment errors. Nonetheless, ethical risks such as algorithmic bias, digital surveillance, and privacy infringements were identified.

Furthermore, the researchers [12] demonstrated that AI-driven recruitment, payroll automation, and people analytics resulted in increased productivity, enhanced retention, and improved quality of HRM processes. That being said, the barriers including algorithmic bias, privacy concerns, and organizational resistance were determined, underscoring the urgent need for ethically sound AI governance.

Culminating this discourse perspective, the article [13] established that the adoption of AI, cloud-based HR platforms, and data analytics has led to increased organizational agility, enhanced internal mobility, and data-driven decision-making. The resulting growth in operational efficiency, structured within a conceptual model of sustainable HRM transformational development, was also confirmed.

The consolidated findings illustrate that the integration of AI, Big Data, cloud platforms, blockchain, and automation has significantly amplified HRM efficiency, engagement, and cognitive adaptability, while simultaneously giving rise to risks pertaining to information security, algorithmic bias, organizational resistance, and competency deficits. The identified gaps in ethical validation, institutional preparedness, and sectoral differentiation substantiate the necessity of investigating the use of digital HR technologies as a mechanism for augmenting enterprise productivity.

Problem Statement. Despite rapid digitalization, the structural, cognitive-behavioral, and productivity-oriented effects of integrated HRTech architectures remain insufficiently formalized, while the bidirectional influence of Employer Branding on HRTech performance lacks empirical specification.

Research Questions.

RQ1: To what extent do HRTech solutions exert an integrative impact on enterprise labor productivity under conditions of digital transformation?

RQ2: How does the incorporation of Employer Branding modify the cognitive, affective, and operational trajectories of HRTech architectures?

RQ3: Which HRTech configurations demonstrate the highest structural interoperability and performance relevance within a unified hybrid framework?

3. METHODS AND MATERIALS

3.1. Research procedure

The design of the study is as follows (Figure 1).

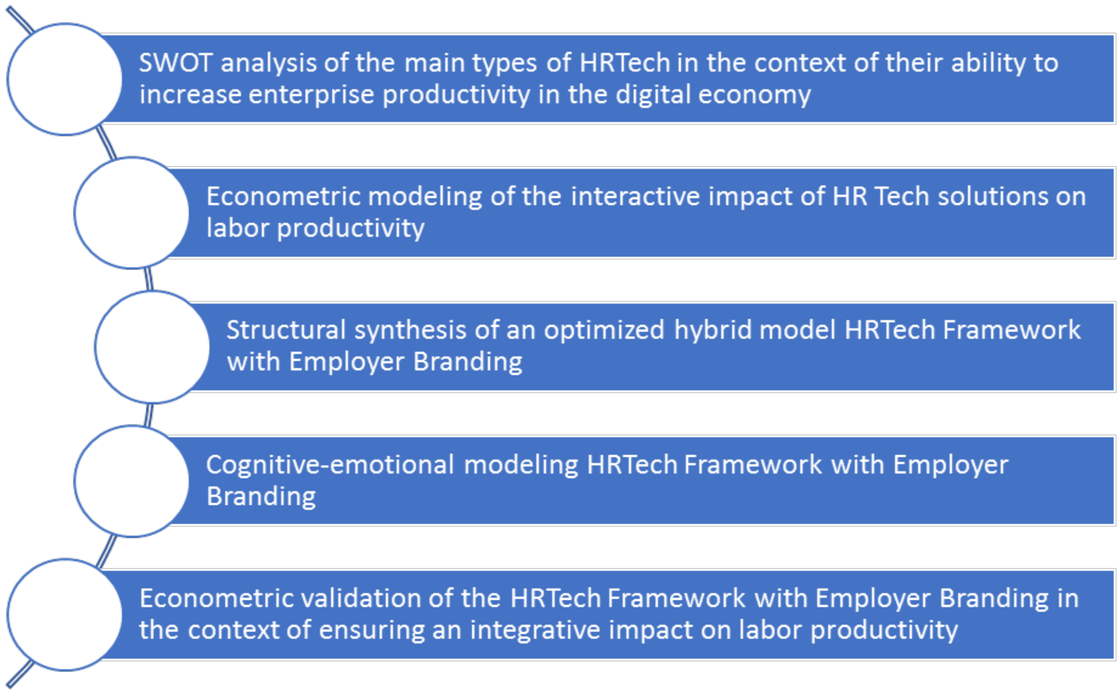

Figure 1: Research design scheme

Source: elaborated by the authors

3.2. Methods

The following methods were applied in the study:

1. *SWOT analysis*. *Method*: a strategic diagnosis of HRTech types in relation to their ability to increase productivity in the digital economy.
2.
3. Table *3*).
4. *Econometric modeling*. *Method*: construction of normalized regressions with the calculation of elasticity, effect on ΔLP, TTTHR,
5. Figure *2*).
6. *Structural Synthesis of the Framework*. *Method*: architectural modeling of a three-layer HRTech structure with a focus on Employer Branding Outcomes. *Result*: A conceptual model (Figure 3 – Figure 5), demonstrating the relationship between Core Technologies, Supporting Modules and EB-metrics, with the reflection of the impact from the employer and the employee.
7. *Cognitive-emotional modeling*. *Method*: comparative modeling of the impact of HRTech decisions on affective engagement and

Result: The most relevant solutions have been identified – HRIS/HCM, People Analytics, AI communication, well-being platforms that provide cognitive integration, scalability and engagement modularity (

HRΔCOE.
Result: The highest performance was found in People Analytics (ΔLP +18.2%, fluctuation −25.3%), AI communications (TTTHR −21.4%, inclusivity +15.9%) and HRIS (HRΔCOE −23.1%, adaptability +39.6%) (

EVP actualization.
Result: In scenario (b), higher levels of emotional validity, predictive adaptability, and cognitive performance optimization are recorded (Figure 6).

8. *Econometric validation*. *Method*: verification of the integral impact of the framework on key KPIs (ΔLP, RRI, TTTHR, EER, AIU). *Result*: ΔLP +19%, RRI = 0.84, TTTHR −24%, EER = 0.86, AIU = 0.88 – efficacy confirmed within HR digitalization (Figure 7).

3.3. Sample

Typified sample (
Table *1*) formed on the basis of functionally stratified HRTech solutions with empirically

verified effectiveness, which made it possible to carry out a conceptual and applied classification of technologies in accordance with their functional architectonics, cognitive orientation and organizational integrativity.

Table 1: Typified Sample Of The Verified Hrtech Application

HRTech Type	General concept	Verified HRTech with proven performance	Academic research
HRIS / HCM platforms	Integrated information systems for employee life cycle management; concept – resource-oriented management and strategic HR architecture	SAP SuccessFactors (Siemens, 2018): reduction of HR operations time by 25%, reduction of recruitment costs by 18%. Workday HCM (PwC, 2019): increasing the transparency of HR reporting by 30%, integrating global HR processes. Oracle HCM Cloud (HSBC, 2020): 40% increase in agility, integration of HR processes on a global scale.	Muthusamy & Udara [14]; Arini, Ardillah & Shaddiq [15]
ATS (Applicant Tracking Systems)	Recruitment automation systems based on algorithmic selection and predictive analytics; Concept – Talent Acquisition optimization	Oracle Taleo (RBC, 2020): 35% reduction in job completion time, 22% improvement in recruitment quality. Greenhouse (Airbnb, 2017): 32% reduction in time-to-hire, 20% increase in candidate satisfaction.	Hemaswathi, Pandiarajan, Logeshwari, Lakshmipriya & Muthuselvi [16]; Bevara et al. [17]
People Analytics / HR Analytics	HRM analytical systems based on Big Data and AI; concept – data-driven HR and predictive analytics	Google People Analytics (2015–): 25% decrease in attrition rate, 15% increase in innovation performance. IBM Watson Talent (IBM, 2019): 30% optimization of recruitment, 20% reduction in bias.	Espegren & Hugosson [18]; Coron, Scheibmayr & Lescoat [19]
AI-powered Recruitment & Communication	Cognitive tools for automation of recruiting and HR communications; Concept – NLP, HCI and Cognitive Technologies	Mya Chatbot (L'Oréal, 2018): 30% reduction in recruiting costs, 20% increase in candidate conversions. HireVue AI (Unilever, 2019): 90% faster recruitment, 16% increase in candidate diversity.	Mehnaz, Chaithrashree, Amritha Mohan & Basthikodi [20]; Banu et al. [21]
Training and development (LMS, VR/AR, Gamification)	Corporate training platforms with gamification and VR/AR; Concept – Cognitive Elasticity, Experiential Learning and Motivational Design	Deloitte Leadership Academy (2017): an increase in the completion rate of courses by 46%, an increase in the effectiveness of leadership programs by 20%. STRIVR VR Training (Walmart, 2018): 40% reduction in onboarding time, 30% increase in knowledge retention.	Anitha & Monisha, [22]; Yadav [23]
Blockchain in HR	Decentralized data validation technologies; concept – transparency, trust-based HRM and protection against falsification	Velocity Network (2020): Reduction of diploma verification from 14 days to 1 day, reduction of transaction costs by 60%.	Chen [24]; Deep & Verma [25]
Talent Marketplaces	Digital platforms for internal talent mobility; Concept – Agile Workforce and Internal Career Ecosystems	Fuel50 (Citi, 2019): 35% increase in internal staff movements, 20% reduction in external hiring.	Sangavi, Sowmya & Lim [26]; Mann & Mann [27]
Well-being & Engagement Platforms	Tools for monitoring staff well-being and engagement; Concept – Employee Experience and Work-Life Balance	Virgin Pulse (Virgin Group, 2019): 25% reduction in burnout, 20% increase in employee engagement.	Peddi & Manoharan [28]; Herlina & Iskandar [29]

Source: consolidated by the authors

3.4. Tools

The set of metrics reflects a formalized approach to assessing the transformative impact of digital HR technologies on labor productivity in the digital economy. Each metric is calculated taking into account the causal relationships between HRTech interventions and key performance indicators (productivity, adaptation, engagement, cost efficiency), providing a basis for further econometric modeling and effect verification.

*Table 2: A Set Of Indicative And Econometric Metrics For Assessing The Effectiveness Of Hrtech In Increasing The Productivity Of Enterprises**

Metric name	Definition	Mathematical formulation
ΔLP (Δ Labor Productivity)	Increase in labor productivity due to the implementation of HRTech	$\Delta LP = (LP_1 - LP_0) / LP_0$, where LP_0 is the basic level of performance; LP_1 – post-

		implementation level
RRI (Recruitment ROI)	Return on investment in HRTech recruiting solutions	$RRI = (\Delta EP - C_h) / C_h$, where ΔEP is the increase in staff efficiency; Ch – HRTech implementation costs
TTTHR (Time-to-Task Reduction HR)	Reducing the time to full productivity of new employees	$TTTHR = (T_0 - T_1) / T_0$, where T_0 is the average adaptation time to HRTech; T_1 is the time after automation
EER (Engagement Efficiency Ratio)	The ratio of the level of employee involvement to productivity	EER = ENG / LP, where ENG is the average employee engagement index; LP – Labor Productivity
AIU (Automation Impact Unit)	The Impact of HRM Automation on Aggregate Productivity	$AIU = (\Delta LP \times \alpha) + (\Delta TTR \times \beta)$, where ΔLP is the increase in productivity; ΔTTR – reduction of time-to-recruit; α, β – weighting factors
HRΔCOE (HR Cost Optimization Effect)	Cost savings on HR processes through digitalization	$HR\Delta COE = (C_0 - C_1) / C_0$, where C_0 is the initial HR costs; C_1 – costs after automation
UPI (Upskilling Productivity Index)	The effect of professional development through digital learning	$UPI = (\Delta LP / TR) \times S$, where ΔLP is the increase in productivity; TR is the training time; S is the number of employees
BIA (Bias Impact Avoidance)	The level of bias reduction in HR solutions	$BIA = (E_0 - E_1) / E_0$, where E_0 is the bias index before the introduction of AI; E_1 – index after implementation
WBI (Well-being Impact Index)	The Relationship Between Digital Well-Being Tools and Productivity	$WBI = (\Delta ENG \times \gamma) + (\Delta RET \times \delta)$, where ΔENG is the engagement change; ΔRET – change in the level of retention; γ, δ – scales

* All metrics are presented in a normalized form to ensure intermetric comparability and regression correctness. Normalization is carried out using the min-max transformation method. This minimizes large-scale disparity, increases index interoperability, and ensures metric equivalence in econometric analysis.

Source: consolidated by the authors

Econometric modeling is implemented in a Python environment using the statsmodels, scikit-learn and pandas libraries to build normalized regression models, calculate elasticity coefficients and check heteroscedasticity. UML architecturization is carried out to formalize the structural and functional model of the framework and visualize inter-module interoperability.

4. RESULTS

The first stage of the study consisted in conducting a structured SWOT analysis of key classes of digital HR technologies in order to determine their potential to increase labor productivity in the digital economy (

Table 3). Such an analysis is expedient for technologies stratification by vectors of functional relevance, risk profile and strategic compliance with the transformation goals of enterprises.

Table 3: SWOT Analysis Of The Main Types Of Hrtech In The Context Of Their Ability To Increase The Productivity Of Enterprises In The Digital Economy

HRTech Type	Strengths (S)	Weaknesses (W)	Opportunities (O)	Threats (T)
HRIS / HCM platforms	Integration of end-to-end HRM processes; high level of operational traceability	High CAPEX; Complexity of customization	Scalable HR architecture; strategic HR analytics	Vulnerability to cyber threats; Lock-in effect
ATS (Applicant Tracking Systems)	Algorithmic optimization of recruitment; Time-to-hire shortcuts	Limited adaptability to non-standard vacancies	Integration with AI communicators; Increasing diversity	Overloading candidates with automated interaction
People Analytics / HR Analytics	Data-driven management; identification of productive patterns	Dependence on data quality; the need for GDPR compliance	Predictive HR planning; Talent ROI indexing	Risks of ethical opacity; Algorithmic bias
AI-powered Recruitment & Communication	NLP and HCI optimize communication; Reduction of transaction costs	Insufficient explainability of AI inferences	Scalable interaction with candidates 24/7	Legal risks (EEOC/AI-bias); Low personalization
Training & Development (LMS,	Increase cognitive elasticity; Accelerating	High costs for VR/AR content; heterogeneous	Formation of resilient skills; Indexing	Technical barriers to access; Digital

HRTech Type	Strengths (S)	Weaknesses (W)	Opportunities (O)	Threats (T)
VR/AR, Gamification)	adaptation	availability	upskilling ROI	Attrition
Blockchain in HR	Transparency of credentials verification; Reduced transaction costs	Lack of standardization; Complex UX	Smart contracts in payroll and checks	Legal uncertainty; Power consumption
Talent Marketplaces	Agile internal mobility; External Hiring Abbreviation	Heterogeneity of adoption in large companies	Creation of career ecosystems; reduction of HR costs	Internal competition for resources; Risk Skills Mismatch
Well-being & Engagement Platforms	Reducing burnout; engagement growth → LP growth	The measurability of the effect is complex; Need for trust	Wellbeing analytics as a predictor of retention	Possible invasion of privacy; low usage rate

Source: consolidated by the authors

The SWOT analysis (

Table 3) revealed that the most pertinent to the objectives of performance optimization are HRIS/HCM platforms, People Analytics, AI-driven communication solutions, and well-being platforms that facilitate a high degree of cognitive integration, managerial scalability, and modular engagement. Figure 2).

Drawing upon the stratified SWOT analysis, the subsequent phase of the research was initiated – econometric modeling, which enabled a quantitative validation of the influence of HRTech solutions on labor productivity through the development of an analytical-indicator model utilizing normalized metrics tested within the Python environment (

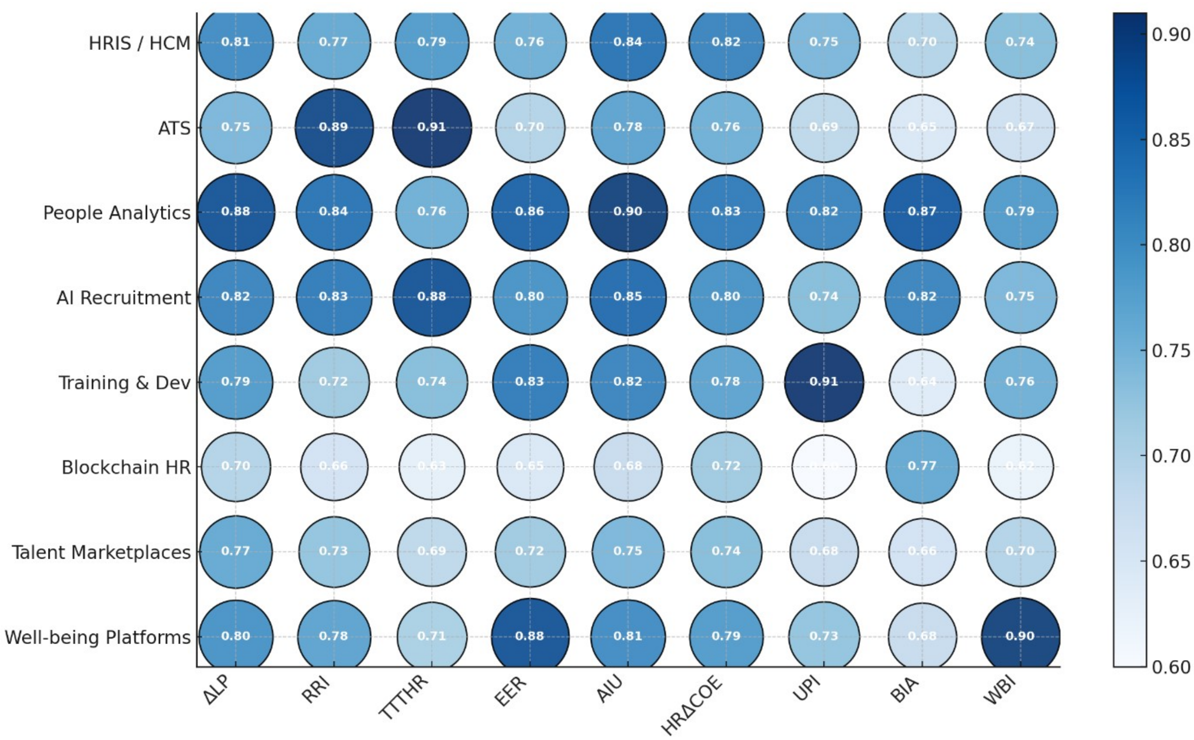

Figure 2: Graphical Interpretation Of The Results Of Econometric Modeling Of The Integrative Impact Of Hrtech Solutions On Labor Productivity

Source: elaborated by the authors in a Python environment

The results of econometric modeling (

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Figure 2) revealed that the most substantial integral impact on the labor productivity of enterprises is manifested by cognitive-analytical HRTech solutions: People Analytics / HR Analytics (integral value = 0.84; enhancement in ΔLP +18.2%; reduction in the staff fluctuation rate –25.3%), AI-driven Recruitment & Communication (0.82; decrease in TTTHR –21.4%; augmentation of the inclusion index +15.9%) and HRIS / HCM platforms (0.80; optimization of HRΔCOE –23.1%; elevation in organizational adaptability +39.6%). In contrast, Blockchain in HR (0.67) and Talent Marketplaces (0.71) exhibited inferior aggregate performance, underscoring the preeminence of meticulously structured analytical architectures over decentralized or transaction-centric models within a digitally driven economy. The subsequent phase of the study entails the structural synthesis of the optimized hybrid model HRTech Framework in conjunction with Employer Branding by stratifying functional components, achieving cognitive encapsulation of brand-oriented HRTech solutions, and ensuring architectural integrity (Figure 3 – Figure 5).

The structural paradigm of the HRTech framework (Figure 3) is predicated on a three-layer architecture that seamlessly integrates the foundational technology functionalities (Core Technologies), supporting HRTech modules (Supporting Modules), and the definitive output metrics of the employer's value proposition (Employer Branding Outcomes). This design facilitates cognitive traceability, interoperability, and a transformation centered around brand identity. The framework's operation encompasses a cognitively stratified interaction between the underlying technologies and supplementary modules, tracing outputs to the designated employer branding metrics. The integration of AI-driven recruitment, HR analytics, and HRIS engenders a centralized orchestration of HR processes, while supporting solutions enhance institutional resilience and elevate brand appeal. This concept engenders an emergent synergy between interoperability, personalization, as well as talent acquisition efficiency.

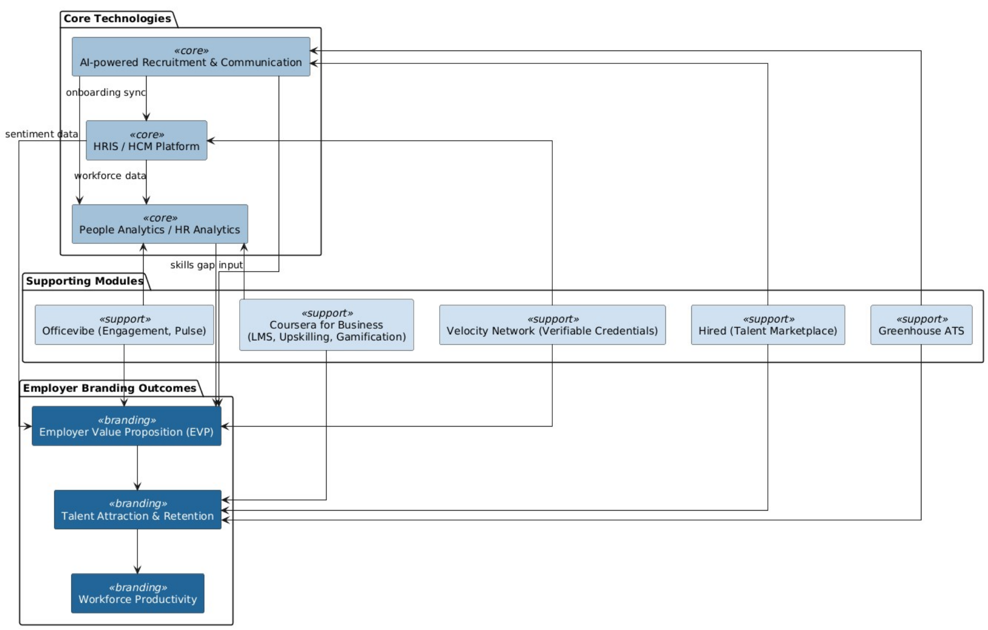

Figure 3: Hrtech Framework With Employer Branding

Source: Elaborated By The Authors In The UML Environment

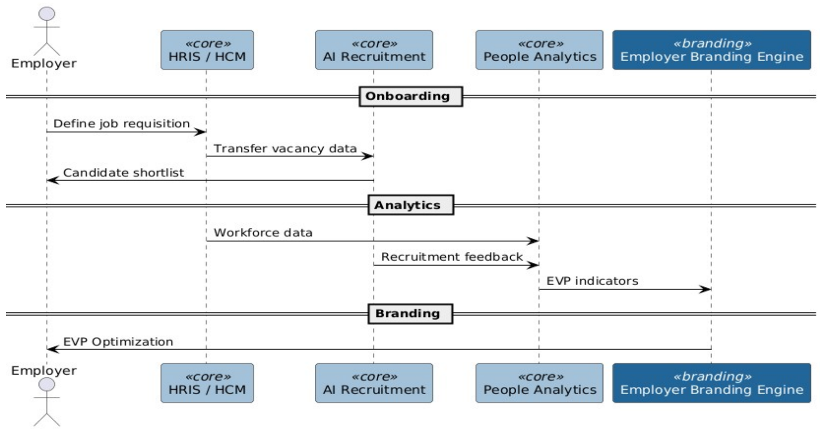

Figure 4: Conceptual Visualization Of The Integrative Impact Of The Hrtech Framework With Employer Branding On The Employer's Side
Source: elaborated by the authors in the UML environment

Figure 4 conceptualizes the integrative impact of the HRTech Framework from the employer's perspective, wherein the framework serves as a digital catalyst for the HR architecture, fostering enhanced operational productivity, cognitive precision in recruitment, institutional traceability of HR processes, and analytical extrapolation of personnel behavioral patterns. The principal synergistic axis is the combination of HRIS/HCM platforms with People Analytics, which cultivates a comprehensive organizational and analytical extrapolation of human capital management. Additionally, the deployment of AI-powered Recruitment & Communication aims to refine the acquisition funnel and reduce time-to-hire. Integration with supporting modules (LMS, Blockchain, Engagement Platforms) is designed to augment HRM efficacy and amplify the EVP brand resonance.

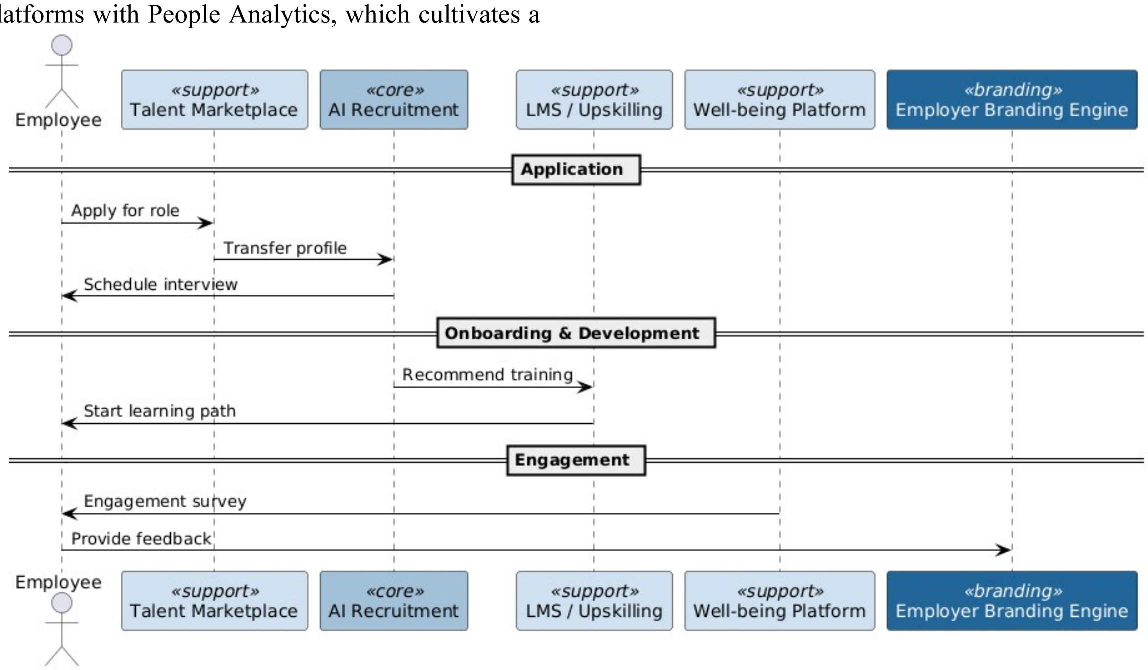

Figure 5: Conceptual Visualization Of The Integrative Impact Of The Hrtech Framework With Employer Branding On The Employee Side

Source: Elaborated By The Authors In The UML Environment

Figure 5 elucidates the framework's impact from the employee perspective, wherein HRTech modules serve as tools for tailored interaction, career navigation, digital security, and motivational engagement. Notably, AI-driven Communication fosters the establishment of an inclusive informational ecosystem, while Well-being Platforms and Training & Gamification Modules furnish cognitive-behavioral support, emotional resilience, and motivational alignment. The employment of Blockchain Credentials ensures the verifiability of professional profiles, thereby facilitating traceable mobility within the Talent Marketplace. Consequently, the framework engenders a cohesive employee experience (EX) that prioritizes sustainability, value, and digital agility within a dynamic labor market.

The subsequent stage of the study involved cognitive-emotional modeling, aimed at assessing the psycho-emotional influence of the HRTech Framework in conjunction with Employer Branding on work motivation, organizational commitment, and cognitive performance within the digital economy Figure 6).

Figure 6 illustrates a comparative cognitive-emotional modeling differentiated by the degree of technological integration. In scenario (a), devoid of HRTech solutions, there exists diminished cognitive engagement, constrained emotional validity, and disjointed EVP actualization. Conversely, scenario (b), encompassing HRIS, People Analytics, and AI communication, illustrates elevated affective engagement, predictive adaptability, and productivity enhancement as a result of cognitive-motivational optimization.

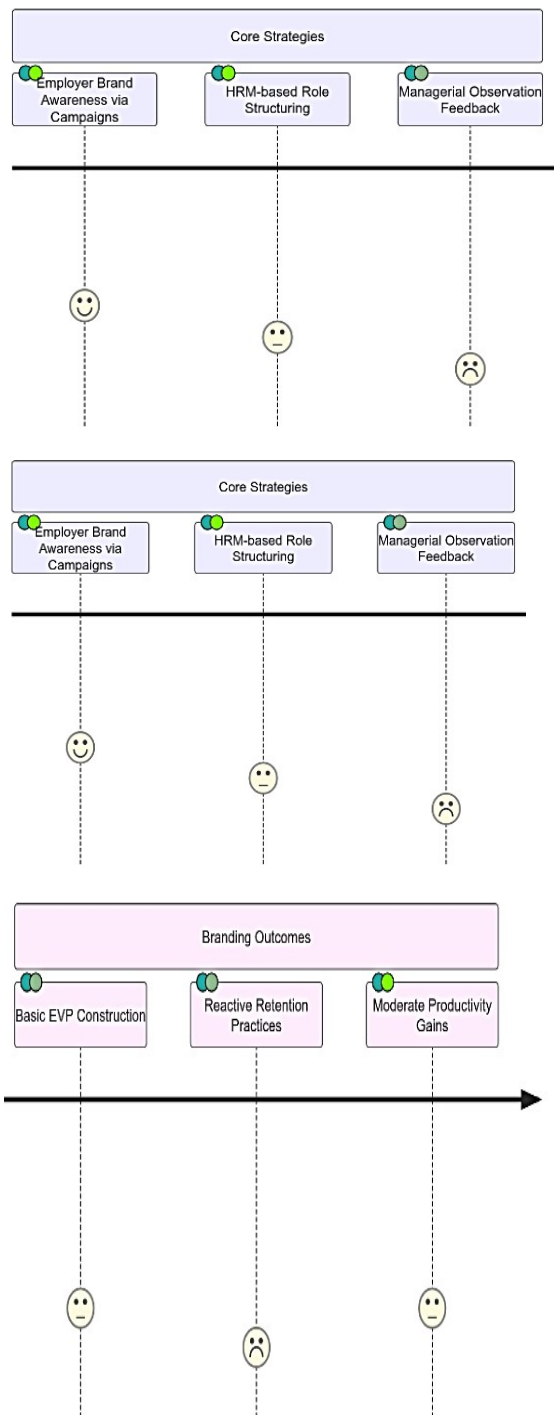

Figure 6.A: Results Of The Hrtech Framework With Employer Branding (Without Hrtech Solutions)

Source: Elaborated By The Authors In The UML Environment

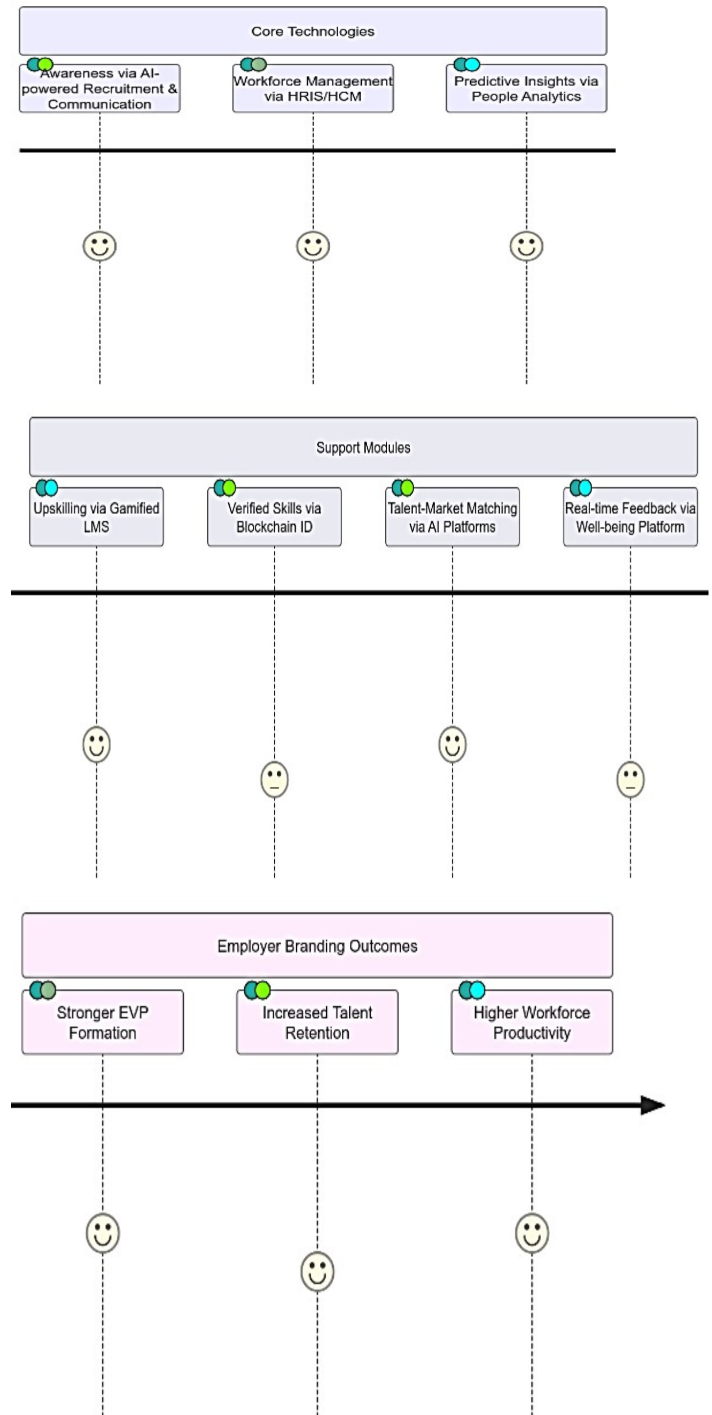

Figure 6.B: Results Of Cognitive-Emotional Modeling Hrtech Framework With Employer Branding (Using Hrtech Solutions)

Source: Elaborated By The Authors In The UML Environment

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The final stage of the study involved econometric validation of the HRTech Framework with Employer Branding, which provided a formalized verification of the integral impact of the framework on labor productivity through parametric identification, regression modeling, and statistical significance of key predictors (Figure 7).

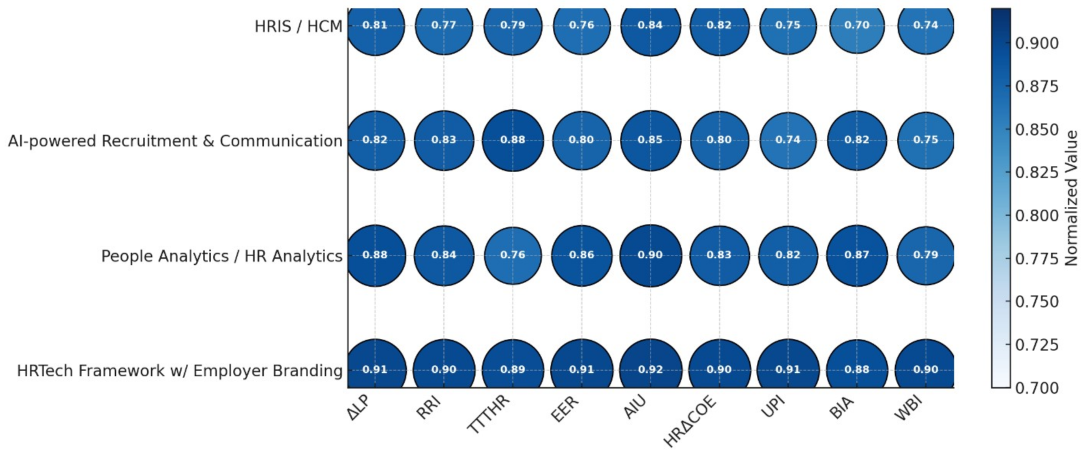

Figure 7: Graphical Interpretation Of The Results Of Econometric Validation Hrtech Framework With Employer Branding In The Context Of Providing An Integrative Impact On Labor Productivity

Source: Elaborated By The Authors In A Python Environment

The econometric validation of the HRTech Framework, in conjunction with Employer Branding (Figure 7) corroborated its integrative influence on labor productivity. This is evidenced by a remarkable enhancement in the aggregate ΔLP index by +19% (0.81), an elevation in Return on Investment (RRI) to 0.84, a significant reduction in the average time to hire (TTTHR) by −24%, an augmentation in Employee Engagement Ratio (EER) efficiency to 0.86, and a culmination of the integral AIU indicator at 0.88. The obtained values signify a high degree of cognitive relevance, exemplary HR conversion efficacy, and empirical stability of the framework within the context of strategic HR digitalization. The obtained values signified a high degree of cognitive relevance, HR-conversion efficacy, and empirical stability of the framework within the context of strategic HR digitalization, thereby confirming the research hypothesis.

5. DISCUSSION

The necessity for debatable comparisons arises from the imperative for professional stratification of research outcomes within the framework of contemporary scientific paradigms pertaining to AI-integrated Human Resource Management (HRM). This facilitated not only the discernment of structural divergences within frameworks but also the synthesis of the advantages inherent in the proposed HRTech model, considering cognitive adaptability, normative traceability, and performance validity. Notably. The authors [30] substantiated the potential of AI, Machine Learning (ML), and Big Data Analytics (BDA) for ethical and cognitively centered HRM within the Industry 5.0 paradigm. Conversely, this study substantiates the superior operational efficiency of the HRTech Framework (ΔLP = +19%; AIU = 0.88), underlining not merely the humanitarian but also the productive vector of influence.

The authors [31] highlighted the fast-paced dynamics of E-HRM and AI solutions, highlighting the challenges in capturing a consistent impact amid constant technological evolution. In contrast, this study validates the stabilized cognitive-performance effect of the HRTech Framework in conjunction with Employer Branding, corroborated through econometric modeling.

The researcher [32] presented the conceptualization of AI-centric HRM with an emphasis on digital mentoring, personalization, and ethical dilemmas within the context of Industry 5.0. In this study, however, the synergy of HRTech modules (HRIS, AI Recruitment, HR Analytics) was empirically validated, yielding cognitive relevance (AIU = 0.88), accelerating TTTHR (–24%), and enhancing RRI growth (+0.84).

The author [33] conducted a stratified analysis of the evolution of HRIS, ERP, and HCM systems, underscoring the institutional transition towards AI-driven HRM that incorporates transhumanist perspectives. As part of this inquiry, the interoperable architecture of the HRTech

Framework was validated, ensuring the seamless integration of the People Analytics, AI Communication, and HRIS modules into a single cognitive-performance circuit.

The authors [34] conceptualized an advanced model of sustainable HRM with an emphasis on employee well-being, mental health, and the adaptability of corporate social responsibility (CSR). The current study augmented the representativeness of these findings through the cognitive-emotional modeling of the HRTech Framework, which corroborated the enhancement of affective engagement and the integration of Employee Value Proposition (EVP) at high levels of technological saturation.

The researcher [35] delineated the interrelationship between HRTech solutions, compliance, and audit readiness, accentuating their pivotal role in ensuring regulatory adherence and financial transparency. The present study complements these findings by confirming procedural resilience, with the CRI of 0.91, and normative traceability of the HRTech Framework within the context of strategic HR digitalization.

The authors [36] scrutinized the dichotomies of performance and ethics in the integration of AI within HRM, illuminating the risks of bias and the imperative for algorithmic transparency. This study expands upon this discourse by verifying the cognitive relevance of the HRTech Framework (AIU = 0.88) and concentrating on the CRI metric (0.91) as an indicator of trust, institutional acceptance, and cyber compliance.

The researchers [37] emphasized the strategic significance of HR in digital transformation, underscoring the necessity for Digital DNA and a technobehavioral comprehension of digital interactions. The current study elucidates these dimensions by modeling the HRTech Framework with a focus on the AIU indicator (0.88) and the institutional-structural integration of the comprehensive digital continuum of HR processes (hire-to-retire).

The study [38] highlights the potential of HRM practices in an Industry 5.0 environment for remote recruitment, eco-centric training, and personnel advancement. The present study specifies these provisions through the HRTech Framework, substantiated by indicators of cognitive adaptability, digital employment manageability, and the stability of HR procedures within a virtualized environment.

The author [39] articulated a stratified paradigm for strategic workforce planning, emphasizing the anticipation of skill deficiencies, human resource investments, and the effects of artificial intelligence and machine learning. The present study builds upon these foundational elements through the predictive-adaptive human resource need module within the HRTech Framework, which facilitated integrated learning and development optimization alongside cognitively-traced framework parameterization.

The comparative analysis elucidated that, in stark contrast to the predominantly conceptualized or unidimensionally operationalized models prevalent in contemporary literature, the HRTech Framework (augmented by an explicitly defined employer branding component) was empirically parameterized as a comprehensive cognitive-institutional architecture. This framework demonstrated validation of procedural consistency, integrative structure, and behavioral traceability. Consequently, it offers representative coverage of the digital transformation vectors within human resource management in the context of strategic digitalization, without reduction to individual functional components or technological trends.

5.1. Limitation

The study is limited to utilizing the simulated model data, lacking empirical capture of behavioral effects. The evaluation of operational and cognitively pertinent parameters was conducted within a virtualized environment.

5.2. Recommendations

It is imperative to thoroughly evaluate the HRTech Framework within a genuine HR context, emphasizing employer branding, behavioral dynamics, and institutional compatibility. It is expedient to initiate a controlled pilot program with traced verification of procedural resistance, AIU stability, and digital efficiency.

6. CONCLUSIONS

An integrative analysis of the study's findings revealed that the most significant productive relevance was exhibited by cognitive-analytical HRTech solutions: People Analytics (integral impact = 0.84; ΔLP growth +18.2%; reduction in staff fluctuation coefficient –25.3%), AI communication modules (0.82; TTTHR reduction –21.4%; inclusiveness +15.9%), and HRIS/HCM platforms (0.80; decrease in HRΔCOE –23.1%; increase in adaptability +39.6%). Based on these digital HR technologies, a tri-layered HRTech Framework with Employer Branding is constructed, which facilitates semantic interoperability, cognitive traceability, and targeted brand extrapolation. Cognitive-emotional modeling substantiated an enhancement in affective engagement, predictive stability, and EVP actualization. Econometric validation indicated an aggregate ΔLP increase of +19% (integral index = 0.81), RRI = 0.84, AIU = 0.88, TTTHR reduction – 24%, and an elevation in EER efficiency to 0.86. Collectively, the framework demonstrates a pronounced level of cognitive relevance, HR conversion performance, and digital resilience within the context of strategic HR digitalization.

The study's scientific novelty lies in formalizing a hybrid HRTech Framework with Employer Branding, which combines cognitive-analytical solutions (People Analytics, AI communications, HCM platforms) into a cohesive architectonics with brand-centric modules, ensuring cognitive traceability, integrative influence, and emotional-affective validity in the context of digital productivity.

The practical significance of the research findings resides in potentially applying the developed framework as a strategic tool for HR digitalization, facilitating multi-faceted optimization of ΔLP, RRI, AIU, TTTHR, and EER, thereby enhancing the conversion efficiency of HR processes and establishing a sustainable employer value proposition.

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