Marketing, Management & E-business

FROM HUMAN DEVELOPMENT TO INNOVATION OUTCOMES: A CROSS–COUNTRY AND INCOME GROUP ANALYSIS

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EXTENDED ABSTRACT

Purpose Innovation and human capital are considered the two main pillars of contemporary economic growth (Aiting *et al.*, 2022). Additionally, certain scholars consider that human capital is an innovation engine (Acemoglu, 1996; Aghion and Howitt, 1998). However, the evidence from developing countries shows that the increased investment in human capital has not brought the corresponding innovation growth (Li and Nan, 2019). In this context, this paper investigates the path from human capital, through innovation inputs and processes to innovation outcomes, by utilizing data from the Digital Evolution Index (2025) for 125 countries over the timespan 2008-2023. More specifically, this research examines whether human development presented as the "state of human condition" and measured within the Digital Evolution Index, translates into higher levels of innovation inputs, processes, and finally innovation outcomes, i.e., technological and innovation outputs that reflect society's digital progress. In this framework, human development is conceptualized as a set of socio-economic conditions that enable individuals and communities to adopt, adapt, and benefit from digital technologies.

Design/methodology/approach Panel regressions, i.e., Fixed Effects and Random Effects models, were applied to control for unobserved country heterogeneity. The Hausman Test statistics with 1.87 and a p-value of 0.76 showed that Random Effects estimators are more consistent. Additionally, to complement the causal inference, a Random Forest Regressor was used in order to capture non-linear patterns and provide feature importance analysis. Also, to account for structural differences across development levels, income group classifications by the World Bank (low, lower–middle, upper–middle, high) were included as additional predictors in the Random Forest Model. In simple terms, to test whether the development stage modifies the path. This study uses a combination of econometrics with machine learning models in order to improve predictive accuracy, provide more accurate and robust predictions (Khan and Wyrwa, 2025).

Findings Panel regression confirms that the improvements in human development (measured and presented as human condition) are significantly associated with greater innovation inputs, which in turn foster processes and eventually outcomes. In the preferred Random Effects model, human development, inputs, and processes are all positive and significant predictors of outcomes.

The Random Forest model has a strong predictive performance ($R^2 > 0.70$, MAE low relative to outcome scale). It was trained on 80% of the sample and tested on the remaining 20%. The feature importance analysis provides insights into the relative predictive power of each

10.47063/EBTSF.2025.0032
http://hdl.handle.net/20.500.12188/34513

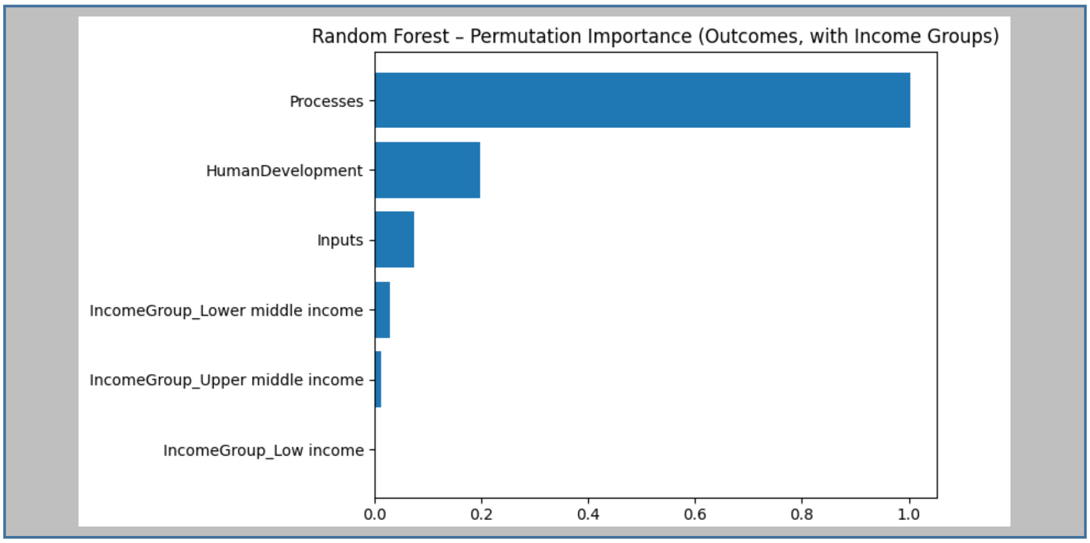
analyzed determinant, where both impurity–based and permutation importance (see Figure 1) confirm that:

- Innovation processes emerge as by far the most influential predictor of innovation outcomes (accounting for the vast majority of predictive power, i.e., close to 1.0 in permutation importance)
- State of human development contributes modestly (~0.20)
- Innovation inputs are weaker (~0.07)
- Income groups contribute modestly, with Lower-middle (~0.03) and Upper-middle (~0.01) income classifications adding small predictive value, while Low-income countries show negligible importance.

In summary, these findings show that while structural development levels matter, actually the strength of processes rather than income group status per se that primarily explains the cross-country differences in innovation outcomes.

Originality/value This research combines panel regression and machine learning to empirically trace the path from human development, through innovation inputs and processes to outcomes. Findings suggest that investments in human development and innovation inputs are necessary but insufficient unless supported by robust processes, i.e. "systems in place which can facilitate the development of innovative ideas and practices" (Chakravorti *et al.*, 2025), that translate inputs into tangible outputs, measured through ICT Service Exports (%), ICT Goods Exports (% Total Goods Exports), Apps developed per person, Scientific and Technical Journal Articles etc.

Figure 1: Permutation importance of Predictors for Innovation Outcomes (Random Forest)



(Source: Authors' calculation based on DEI 2025)

Table 1: Panel Regression Results (Dep. variable: Innovation outcomes)

Variable	FE coef. (t)	RE coef. (t)
Human Development	0.311 (3.21)***	0.320 (15.60)***
Inputs	0.101 (2.11)**	0.090 (4.33)***
Processes	0.147 (2.10)**	0.198 (7.69)***
Constant	-0.705 (-0.21)	-2.476 (-2.13)**
R^2 (overall)	0.602	0.630
No.obs	2000	2000

(Source: Authors' calculation based on DEI 2025)

As shown in Table 1, both models fit the data well, indicating that around 60% of the variation in innovation outcomes is explained by the included predictors. Human development is a significant predictor in both FE and RE models, which means that improvements in social readiness, i.e., education, health, and income levels, etc., are strongly associated with higher innovation outcomes. Inputs and processes also show positive and statistically significant effects, highlighting that R&D investments, financial resources, effective institutional and organizational mechanisms, such as digital adoption, collaborative networks, and policy support, are critical in translating human development into tangible innovation results.

Keywords: *Panel regression, Random forest, Digital evolution, Innovation outcomes, Human development*

JEL classification: *O15, O31, O33*

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