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MEASURING THE PROACTIVITY OF DIGITAL LABOR RELATIONS: A COMPOSITE INDEX APPROACH AND EMPIRICAL EVIDENCE FROM UZBEKISTAN

Yusupova Dinara Anvarovna
Independent researcher, Tashkent University of Information Technologies named after Muhammad al-Khwarizmi

Abstract. *Digital platforms, remote work and algorithmic management have changed the organization of work faster than labor law and statistics have adapted. Existing frameworks, including the ILO decent work indicators, the OECD job quality framework and the Online Labour Index, either produce no single value or capture only one side of the employment relationship. This paper proposes the Digital Labor Relations Proactivity Index (DLRPI), which assesses how far a labor relations system adapts to new forms of employment before problems escalate. The index combines fifteen indicators in five blocks: institutional coverage, income, social protection, governance transparency and proactive adaptation. Indicators are normalized with fixed goalposts, block weights mix principal component and expert estimates, and blocks are aggregated geometrically to limit compensation between them. A two-condition rule assigns reactive, transitional and proactive profiles, and the thresholds are calibrated with k-means clustering. The index was applied to Uzbekistan for 2017-2025 using official statistics and a legal coverage index. The DLRPI rose from 0.119 to 0.509, and the country moved from the reactive to the transitional profile in 2023. Most of the growth came from legal and institutional measures, while the income and adaptation blocks stayed below 0.35. Clustering confirmed the normative threshold of 0.40 with a calibrated value of 0.410, and Monte Carlo tests gave an average Spearman correlation of 0.992. The income block has the largest gap and highest marginal effect. The paper argues that platform income reporting and a minimum pay guarantee should be combined with reskilling linked to automation risk.*

Keywords: *proactivity, digitalization, platforms, employment, informality, wages, index, clustering, robustness, Uzbekistan.*

INTRODUCTION

Digital technologies are changing the way work is organized and paid for. Next to the classic employment relationship, which rests on an employment contract, a fixed workplace and direct supervision, work arranged through digital platforms, remote work and algorithmic management has grown quickly. According to the International Labour Organization (ILO, 2021), the number of online and location-based platforms rose from 142 in 2010 to more than 777 in 2020. The World Economic Forum (WEF, 2025) expects 39 percent of workers' existing skills to be transformed or become outdated between 2025 and 2030. Regulation has started to respond. In June 2026 the International Labour Conference adopted Convention No. 193 on decent work in the platform economy, the first international labour standard written for this kind of work (ILO, 2026).

National responses so far follow two broad models. In the protection-based model the state leaves the worker's status unchanged but places social contribution, insurance and representation duties on the platform. In the data-based model the state first obliges platforms to report on their

workers and only then designs protection; Estonia, where platform operators send annual reports to the tax authority by 31 January of the following year, is an example (Estonian Tax and Customs Board, 2024). Neither model has well-developed tools that assess the risk of technological change in advance and launch adaptation measures on time. Regulation still reacts to problems after they surface as disputes or lost contributions. Measurement is part of the reason. The usual indicators of labor relations, such as the number of registered employees, the average wage and hours worked, were designed for contract employment and miss much of the work done through platforms.

Uzbekistan shows this gap clearly. The share of the population aged 10 and over using the internet rose from 76.6 percent in 2021 to 94.6 percent in 2025, yet information and communication accounted for only 0.73 percent of total employment in 2025, and only about one worker in five used the internet at the workplace (National Statistics Committee of the Republic of Uzbekistan [NSC], 2026). More than 430 thousand self-employed drivers provide taxi services through aggregators (Tax Committee of the Republic of Uzbekistan, 2025), but their hourly income, working time and social contributions are not monitored. The country has digitized several administrative flows, including the electronic registration of employment contracts and the mobile registration of the self-employed. What it lacks is a way to judge whether these steps add up to a system that anticipates change rather than reacting to it.

The aim of this study is to develop a composite index that measures the proactivity of digital labor relations at the level of the national system and to test it on data for Uzbekistan for 2017-2025. The objectives are (1) to move the concept of proactivity from the individual to the institutional level and define its measurable signs; (2) to build an index with transparent rules for normalization, weighting, aggregation and profile classification; (3) to calibrate the profile thresholds and check the robustness of the results on national data; and (4) to identify the block that constrains the index most and the policy lever that addresses it. The object of the study is labor relations carried out through digital platforms, remotely or with digital tools in Uzbekistan, together with the institutions that regulate them. The subject is the methodology for measuring their proactivity.

The study tests the hypothesis that the growth in the proactivity of Uzbekistan's labor relations system has come mainly from legal and institutional measures, while income and adaptive capacity have lagged behind, so that an aggregation method with limited compensation will single them out as the binding constraints. The scientific novelty of the paper lies in four elements: an institutional definition of proactivity with measurable signs; a fifteen-indicator, five-block index with a two-condition profile rule; a data-driven calibration of profile thresholds combined with a first-difference weighting procedure that removes the trend bias of principal component analysis on short time series; and the first quantitative estimate of the proactivity of digital labor relations in Uzbekistan.

LITERATURE REVIEW

Research on the platform economy starts from the question of where the platform sits between the market and the firm. Gawer (2014) treats technological platforms as evolving organizations, or meta-organizations, that coordinate independent agents without turning them into employees. De Stefano (2016) distinguishes two main forms of gig work, crowdwork and work on demand via apps, and warns that describing people as a service pushes labor toward the status of a commodity. The ILO (2021) uses a similar split between online web-based platforms, where tasks are performed remotely, and location-based platforms, where taxi drivers and couriers work in a given physical place. Statistical definitions have moved as well. The 20th International Conference of Labour Statisticians introduced the category of dependent contractors: workers who provide goods or services under commercial contracts and depend operationally or economically on another unit (ILO, 2018).

The same tension runs through research on algorithmic management. Kellogg et al. (2020) show how algorithms direct, evaluate and discipline workers, which turns the workplace into a new contested terrain of control. Wood et al. (2019) found that remote gig workers value their flexibility and task autonomy, yet algorithmic control also leads to low pay, overwork and irregular hours. Meijerink and Bondarouk (2023) argue that HRM algorithms restrict and enable worker autonomy at

the same time, and Vallas and Schor (2020) conclude that platforms keep control over the core of the work process while shifting responsibility for much of the rest to workers. The EU platform work directive responded with a rebuttable presumption of employment and rules on automated monitoring and decision-making (European Parliament & Council of the European Union, 2024). For measurement, this body of work means that the employment relationship has a governance dimension that neither contract status nor income captures.

A second line of research looks at how technology changes the content of jobs. Acemoglu and Autor (2011) proposed viewing jobs as bundles of tasks, some of which machines can take over. Frey and Osborne (2017), treating occupations as indivisible units, estimated that about 47 percent of US employment was at high risk of computerization. Arntz et al. (2017) showed that the share falls sharply once differences in tasks within occupations are taken into account, and Dingel and Neiman (2020) estimated that 37 percent of jobs in the United States can be done entirely at home. For a developing economy the task view is the more practical one: the main constraint is often not automation as such but the lack of skills and legal status needed to move into new tasks. Reskilling and the monitoring of automation risk therefore belong among the measurable features of labor relations.

The concept of proactivity comes from organizational behavior. Frese and Fay (2001) defined personal initiative as a self-starting approach to work that goes beyond what is formally required. Grant and Ashford (2008) described proactivity as anticipatory action that employees take to affect themselves or their environment, and Parker et al. (2010) built a model of proactive motivation around self-initiated, future-focused efforts to bring about change. In a meta-analysis, Fuller and Marler (2009) found that proactive personality is positively related to job performance and career success. All of these studies work at the level of the individual. They share one criterion, though: proactive action starts before the problem appears. This paper carries that criterion over to the labor relations system. A system is treated as proactive if it sets the legal status, the statistical recording and the source of social protection for a new form of employment before that form becomes widespread. It is reactive if it responds only after the problem has turned into open conflict.

Several international frameworks measure parts of this picture (Table 1). The ILO decent work indicators cover ten substantive elements, including social security and social dialogue, but their authors stress that no single statistical indicator, composite or not, can determine whether decent work exists (ILO, 2013). The OECD job quality framework rests on earnings quality, labor market security and the quality of the working environment (Cazes et al., 2015), and it was designed for markets where employee status is clear. The Future of Jobs survey tracks expected changes in skills and occupations (WEF, 2025). SDG indicator 4.4.1 measures the share of people who have carried out specific ICT-related activities (United Nations, 2024), and the Human Capital Index estimates the human capital a child born today can expect to attain by age 18 (World Bank, 2020). The Online Labour Index follows demand for online freelance work by counting projects posted on major platforms (Kässi & Lehdonvirta, 2018).

Table 1.

Existing frameworks for assessing labor relations and job quality

Framework	What it measures	Single value	Limitation for digital labor relations
Decent Work Indicators (ILO)	Statistical and legal indicators for ten substantive elements	No	Not designed for comparison or ranking
Job Quality Framework (OECD)	Earnings quality, labor market security, working environment	No	Algorithmic management and adaptation not covered
Future of Jobs (WEF)	Expected change in skills and occupations	No	Quality of the relationship and protection not measured
SDG indicator 4.4.1	Share of persons with ICT	Yes	Does not show the

(ITU)	skills		relationship in which skills are used
Human Capital Index (World Bank)	Expected human capital of the future workforce	Yes	Not related to current labor relations
Online Labour Index (Kässi & Lehdonvirta)	Demand on online labor platforms	Yes	Income, protection and governance not assessed

Three of the six frameworks give no single value, and the three that do measure only one side of the employment relationship. None of them combines institutional coverage, income, social protection, governance transparency and adaptation in one measure.

The methodology for building such a measure is well developed. The OECD and JRC handbook sets out the steps from the theoretical framework to normalization, weighting, aggregation and robustness checks, and it warns that weights are essentially value judgments whatever method produces them (OECD & European Commission Joint Research Centre [JRC], 2008). The Human Development Index uses fixed goalposts and a geometric mean of dimension indices (United Nations Development Programme [UNDP], 2025), which limits how far a high value in one dimension can offset a low value in another. Saisana et al. (2005) showed how uncertainty and sensitivity analysis can test whether a ranking depends on methodological choices, and Greco et al. (2019) reviewed the trade-offs among weighting and aggregation methods and argued for explicit robustness tests. Principal component analysis is a common source of statistical weights, but on short national time series that share a trend it can reward indicators for moving with the trend rather than for real covariation, a problem this paper takes up below.

The literature thus offers a theory of platform work and algorithmic control, a task-based view of technological change, an individual-level theory of proactivity and a mature toolkit for composite indicators. The missing piece is a measure that brings these together: one that evaluates digital labor relations on all five dimensions in a single scale, calibrates its thresholds on national data, identifies the weakest block and links the result to a concrete policy mechanism.

METHODOLOGY

The study followed the composite indicator approach of the OECD and JRC handbook (2008) and applied it to annual data for Uzbekistan for 2017-2025. The Digital Labor Relations Proactivity Index (DLRPI) does not describe the state of labor relations as such; it measures how far the system adapts in advance to new forms of employment. The index has five blocks with three indicators each (Table 2).

Table 2.

Indicator system of the Digital Labor Relations Proactivity Index

Code	Indicator	Unit	Direction
I_1 Institutional coverage			
x_{11}	Share of digitally employed persons with formal status	%	+
x_{12}	Share of relationships formalized by a written contract	%	+
x_{13}	Time needed to formalize the activity	days	−
I_2 Income and remuneration			
x_{21}	Median hourly earnings relative to the hourly equivalent of the minimum wage	ratio	+
x_{22}	Coefficient of variation of monthly income	%	−
x_{23}	Share of unpaid working time	%	−
I_3 Social protection			
x_{31}	Share of social tax payers	%	+
x_{32}	Share of persons covered by insurance	%	+
x_{33}	Share of months with contributions paid in the last 12 months	%	+
I_4 Governance transparency			

x_{41}	Share of workers informed of evaluation criteria	%	+
x_{42}	Share of workers able to request human review of an algorithmic decision	%	+
x_{43}	Share of workers covered by collective representation	%	+
I_5 Proactive adaptation			
x_{51}	Share of workers covered by digital reskilling	%	+
x_{52}	Share of occupations covered by automation risk monitoring	%	+
x_{53}	Time from the emergence of a new employment form to its legal recognition	years	−

Indicators were normalized with the fixed goalpost method of the Human Development Index (UNDP, 2025) rather than with sample minima and maxima, which shift with every new observation and are sensitive to outliers (OECD & JRC, 2008). Positive indicators were normalized by formula (1) and negative ones by formula (2):

$$z_{ij} = \frac{x_{ij} - L_j}{U_j - L_j} \quad (1)$$

$$z_{ij} = \frac{U_j - x_{ij}}{U_j - L_j} \quad (2)$$

where x_{ij} is the value of indicator j for object i, and L_j and U_j are the lower and upper goalposts (for a negative indicator, the target and the worst acceptable value). Values outside the interval from 0 to 1 were truncated. Percentage indicators used goalposts of 0 and 100 percent; for unpaid time the worst value was one third, in line with the scale of unpaid work reported by the ILO (2021).

Block subindices were arithmetic means of their indicators with equal weights $v_{kj} = 1/3$ (3), since the indicators of one block describe the same dimension and can partly substitute for each other:

$$I_k = \sum_{j=1}^{3} v_{kj}\, z_{kj}, \qquad \sum_{j=1}^{3} v_{kj} = 1 \quad (3)$$

Block weights combined statistical weights from principal component analysis, based on the components with eigenvalues above one (4), with expert weights w_k^E obtained by budget allocation. The two were mixed with $\lambda = 0.5$ in the baseline (5):

$$w_k^S = \frac{A_k}{\sum_{k=1}^{5} A_k}, \qquad A_k = \sum_{m} \theta_m\, l_{km}^2 \quad (4)$$

$$w_k = \lambda\, w_k^S + (1 - \lambda)\, w_k^E, \qquad \sum_{k=1}^{5} w_k = 1 \quad (5)$$

where θ_m is the share of variance explained by component m and l_{km} is the loading of block k on it.

Blocks were aggregated with a weighted geometric mean (6), which limits compensation between them (OECD & JRC, 2008). In practical terms, high income cannot make up for missing social protection or closed governance:

$$R = \prod_{k=1}^{5} (\max\{I_k; \varepsilon\})^{w_k} \quad (6)$$

where R is the DLRPI, ranging from 0 to 1, and $\varepsilon = 0.01$ keeps a zero block from turning the whole index to zero.

A two-condition rule assigns the profile. A system is reactive if $R < 0.40$; transitional if $0.40 \leq R < 0.65$, or if $R \geq 0.65$ while $I_5 < 0.50$; and proactive if $R \geq 0.65$ and $I_5 \geq 0.50$. The second condition

keeps a system with weak adaptation from being classed as proactive. On the profile map, the protection level H (7) is plotted against I_5, with both axes crossing at 0.5:

$$H = \sqrt{I_1 \cdot I_3} \tag{7}$$

The normative thresholds were tested with k-means clustering of standardized vectors of the five subindices, with 200 random starts for each number of clusters. That number was chosen with the silhouette coefficient (8) of Rousseeuw (1987), for which values above 0.5 conventionally indicate a reasonable structure. The calibrated threshold was set at the midpoint between the mean index values of neighboring clusters (9):

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i); b(i)\}} \tag{8}$$

$$\tau_j = \frac{\overline{R}_j + \overline{R}_{j+1}}{2} \tag{9}$$

where $a(i)$ and $b(i)$ are the mean distances from object i to its own cluster and to the nearest other cluster, and $\bar{R}_j$ is the mean index of cluster j.

For each block, the marginal effect on the index (10), the improvement gap (11) and the contribution to the change of the index (12) were calculated. Under geometric aggregation the marginal effect rises as the block value falls, which gives a formal reason to direct resources to the weakest block:

$$\frac{\partial R}{\partial I_k} = \frac{w_k R}{I_k} \tag{10}$$

$$Z_k = w_k (1 - I_k) \tag{11}$$

$$\ln \frac{R_t}{R_{t-1}} = \sum_{k=1}^{5} w_k \ln \frac{I_{k,t}}{I_{k,t-1}} \tag{12}$$

Robustness was checked with Cronbach's alpha, using 0.7 as the acceptance level, and with 1,000 Monte Carlo draws in which λ was uniform on the interval from 0 to 1 and expert weights followed a Dirichlet distribution. Each simulated ranking of years was compared with the baseline by Spearman's rank correlation, with 0.9 as the stability level (Saisana et al., 2005). The principal component analysis was also repeated on first differences of the subindices to see whether the weights reflected a shared trend rather than real covariation.

Uzbekistan has no regular statistics on the income volatility of platform workers, unpaid time, the transparency of evaluation criteria or reskilling coverage. The index was therefore computed with seven official proxies available for every year from 2017 to 2025 (Table 3; NSC, 2026). For the governance block, a legal coverage index (13) was built from the national legislation database (lex.uz) as the share of ten criteria met by the end of each year:

$$x_{41,t} = \frac{1}{10} \sum_{m=1}^{10} d_{m,t} \tag{13}$$

where $d_{m,t}$ equals 1 if criterion m was set by an act adopted by the end of year t, and 0 otherwise. The criteria covered the automated processing of personal data and the electronic registration of employment contracts (2019); the recognition of the self-employed and their registration through a mobile application (2020; Cabinet of Ministers of the Republic of Uzbekistan, 2020); remote work in the Labor Code (Labour Code of the Republic of Uzbekistan, 2022); an online rating of labor rights compliance (President of the Republic of Uzbekistan, 2024); tax withholding by aggregators and the provision of state data to platforms (2025); and two criteria still unmet in 2025, a legal category of platform worker and human oversight of algorithmic decisions.

Table 3.

Proxy indicators used to compute the DLRPI for Uzbekistan

Block	Indicator	Direction	Goalposts (L; U)	Source and note
I_1	Share of the informal economy in GDP, %	−	10; 50	SIAT 1.01.08.0004; 2025 preliminary
I_2	Compensation of employees in GDP, %	+	15; 50	SIAT 1.01.04.0001; 2024 value used for 2025
I_3	Unemployment rate, %	−	2; 15	SIAT 2.02.01.2000 and 2.02.01.1600
I_3	Ratio of female to male unemployment rate	−	1; 3	SIAT 2.02.01.2201 and 2.02.01.2202
I_4	Legal coverage index, 0 to 1	+	0; 1	Formula (13), lex.uz
I_5	Share of computer users aged 10 and over, %	+	20; 100	SIAT 2.03.02.0013
I_5	Share of employment in information and communication, %	+	0; 5	SIAT 2.02.01.1500

Expert weights were set equal at 0.2, as no expert survey was available. With these proxies, the results describe the national labor relations system rather than the platform segment alone.

ANALYSIS AND RESULTS

Principal component analysis of the nine-year series produced a single component with an eigenvalue above one (3.749), which explained 75.0 percent of total variance. The statistical weights were 0.249 for I_1, 0.233 for I_2, 0.020 for I_3, 0.255 for I_4 and 0.243 for I_5. Combined with equal expert weights at $\lambda = 0.5$, they gave final weights of 0.224, 0.217, 0.110, 0.227 and 0.222. The protection block kept a weight of 0.110 in the index, although its statistical weight was close to zero. Table 4 reports the block subindices, the DLRPI, the protection level and the profile for each year.

Table 4.

DLRPI and its blocks for Uzbekistan, 2017-2025

Year	I_1	I_2	I_3	I_4	I_5	DLRPI (R)	H	Profile
2017	0.285	0.123	0.853	0.000	0.229	0.119	0.493	Reactive
2018	0.382	0.123	0.591	0.000	0.233	0.123	0.475	Reactive
2019	0.463	0.180	0.448	0.200	0.232	0.267	0.455	Reactive
2020	0.480	0.177	0.475	0.400	0.247	0.320	0.477	Reactive
2021	0.508	0.191	0.475	0.400	0.291	0.342	0.491	Reactive
2022	0.570	0.211	0.366	0.500	0.299	0.368	0.457	Reactive
2023	0.583	0.306	0.472	0.500	0.308	0.415	0.524	Transitional
2024	0.588	0.274	0.663	0.600	0.322	0.444	0.624	Transitional
2025	0.775	0.274	0.666	0.800	0.336	0.509	0.719	Transitional

The DLRPI rose from 0.119 in 2017 to 0.509 in 2025, a 4.3-fold increase. Under the normative thresholds the country was in the reactive profile from 2017 to 2022 and has been in the transitional profile since 2023. It did not reach the proactive profile in any year. Growth was uneven. The largest jumps came in 2019, from 0.123 to 0.267, and in 2025, from 0.444 to 0.509, and both coincide with increases in the legal coverage index from 0 to 0.2 and from 0.6 to 0.8. The income and adaptation blocks stayed below 0.35 throughout the period (Figure 1). The protection level *H* moved between

0.455 and 0.524 until 2023 and then rose to 0.719 in 2025.

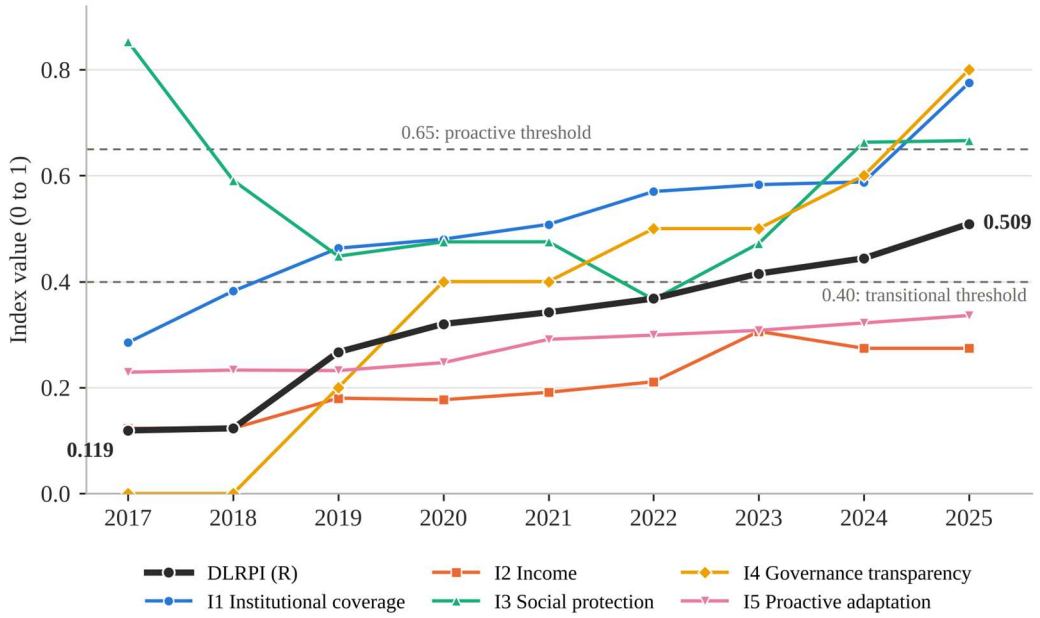


Figure 1. DLRPI and its blocks in Uzbekistan, 2017-2025

Two values call for caution. The protection block reached its highest level in 2017 (0.853) because female unemployment changed from 5.6 percent in 2017 to 11.6 percent in 2018. A doubling within one year is more typical of a change in survey methodology than of an economic process. A similar break affects the institutional coverage block in 2025, when the share of the informal economy in GDP fell from 26.5 to 19.0 percent according to preliminary estimates. If I_1 is held at its 2024 value of 0.588, the 2025 DLRPI is 0.478 instead of 0.509, and the country stays in the transitional profile. With the same weights, an arithmetic aggregation would have given 0.563 for 2025, which is 0.054 above the geometric value.

On the profile map the country stayed in the lower left quadrant, with protection and adaptation both below 0.5, until 2022. In 2023 the protection level crossed 0.5 (0.524) while adaptation remained at 0.308, which moved Uzbekistan into the quadrant where guarantees exist but adaptation lags behind. By 2025 the gap between the two axes had widened, with H at 0.719 and I_5 at 0.336.

For the whole period 2017-2025 the decomposition by formula (12) is distorted. The governance block was zero in 2017, and the floor $\varepsilon = 0.01$ inflates its contribution to 69 percent. The decomposition was therefore run for 2021-2025, when all blocks were above zero. Over these years $\ln R$ increased by 0.400. Governance accounted for 39.4 percent of the change, institutional coverage for 23.8 percent, income for 19.5 percent, protection for 9.3 percent and adaptation for 8.0 percent.

The results of the k-means calibration are given in Table 5.

Table 5.

Calibration of profile thresholds with k-means clustering

Number of clusters	Silhouette coefficient	Cluster composition (years)	Cluster means and thresholds
k = 2	0.443	2017-2019; 2020-2025	$\bar{R}$ = 0.170 and 0.400; τ_1 = 0.285
k = 3	0.436	2017-2018; 2019-2023; 2024-2025	$\bar{R}$ = 0.121, 0.342 and 0.477; τ_1 = 0.232, τ_2 = 0.410
k = 4	0.309	2017; 2018-2019; 2020-2023; 2024-2025	One cluster consists of a single year
Normative rule	not computed	Reactive 2017-2022; transitional 2023-2025	0.40 and 0.65

The two-cluster and three-cluster solutions had almost the same silhouette coefficients (0.443 and 0.436), and both were below the conventional level of 0.5. The three-cluster solution separates 2017-2018, 2019-2023 and 2024-2025 and gives an upper calibrated threshold of 0.410, which differs from the normative 0.40 by 0.01. The proactive threshold of 0.65 could not be calibrated, because no year reached it. The year 2023 lies above 0.410 by its index value but falls into the earlier cluster in the five-dimensional space, which places it on the border between the two profiles. On this basis a two-level rule was adopted. The normative thresholds of 0.40 and 0.65 are kept for absolute assessment, and the calibrated value of 0.232 marks a deep reactive state inside the reactive profile. By this rule, Uzbekistan left the deep reactive state in 2019 and entered the transitional profile in 2023.

Cronbach's alpha calculated across the five block subindices was 0.625, below the 0.7 level, and it rose to 0.817 when the protection block was left out. In the Monte Carlo test the average Spearman correlation between the baseline ranking of years and the rankings produced by 1,000 random weight sets was 0.992, and it exceeded 0.9 in 99.5 percent of draws.

Principal component analysis on the levels of the trending series gave the protection block, which has no trend, a statistical weight of only 0.020. Repeated on first differences, the analysis produced two components with eigenvalues above one (1.876 and 1.308) that together explained 63.7 percent of variance. The corrected statistical weights were 0.213, 0.222, 0.183, 0.191 and 0.190, and the final weights at $\lambda = 0.5$ were 0.206, 0.211, 0.191, 0.196 and 0.195. With these weights the 2025 DLRPI was 0.517 instead of 0.509, the Spearman correlation with the earlier ranking of years was 0.983, and no profile assignment changed. Correlations between the levels of normalized indicators reached 0.96, for example between the informal economy share and the legal coverage index, but in first differences the same pair correlated at only 0.37. The highest correlation of first differences, 0.73, linked the unemployment rate and the ICT employment share, which belong to different blocks, so no indicator was dropped as redundant.

Table 6 shows the improvement gap and the marginal effect of each block in 2025.

Table 6.

Improvement gap and marginal effect of the DLRPI blocks, 2025

Block	I_k	w_k	Gap Z_k, formula (11)	Marginal effect, formula (10)
I_1 Institutional coverage	0.775	0.224	0.051	0.148
I_2 Income	0.274	0.217	0.157	0.402
I_3 Social protection	0.666	0.110	0.037	0.084
I_4 Governance transparency	0.800	0.227	0.045	0.145
I_5 Proactive adaptation	0.336	0.222	0.147	0.336

The income block had both the largest gap (0.157) and the highest marginal effect (0.402). Raising its subindex by 0.01 increases the DLRPI by about 0.004, while the same increase in the protection block adds only 0.0008. Adaptation came second, with a gap of 0.147 and a marginal effect of 0.336. With the baseline weights, raising the income block alone to 0.35 or 0.40 would lift the 2025 index to 0.537 or 0.553. Even if the index exceeded 0.65, the 2025 value of I_5 (0.336) would not meet the second condition of the profile rule.

The current policy instruments show a matching pattern. Of the seven instruments that now govern digital labor relations in Uzbekistan, five serve the formalization and governance blocks: the Unified National Labor System with electronic contracts, the online rating of labor rights compliance, the register of the self-employed, tax withholding by taxi aggregators and the provision of state data to platforms. No instrument exists for income, such as a minimum pay guarantee or income monitoring, or for adaptation, such as an advance assessment of automation risk.

Table 7 shows which block values would bring the country into the proactive profile by 2030. The calculation uses the corrected weights and keeps I_1 and I_4 at their 2025 levels. Progress toward the target is measured by the gap closure coefficient (14), with $R_0 = 0.517$ and $R^* = 0.65$:

$$\eta_t = \frac{R_t - R_0}{R^* - R_0} \quad (14)$$

Table 7.

Target block values, DLRPI and gap closure coefficient

Scenario	I_2	I_3	I_5	DLRPI (R)	η, formula (14)	Condition $I_5 \geq 0.50$
Baseline (2025)	0.274	0.666	0.336	0.517	0.00	Not met
A	0.40	0.666	0.50	0.605	0.66	Met
B	0.45	0.70	0.55	0.638	0.91	Met
C	0.50	0.70	0.55	0.652	1.02	Met
D	0.50	0.75	0.60	0.672	1.17	Met

Raising adaptation to 0.50 and income to 0.40 closes about two thirds of the gap. The smallest combination that meets both conditions is scenario C, with income at 0.50, protection at 0.70 and adaptation at 0.55. For I_5 to reach 0.55, the share of computer users would have to reach 80 percent and the ICT employment share 1.75 percent. On an inertial path, calculated from linear trends of the blocks for 2020-2025 with the legal coverage index held at 0.80, the DLRPI reaches 0.637 in 2030 while adaptation stays at 0.414, so the proactive profile is not reached.

DISCUSSION

The results support the hypothesis. Between 2021 and 2025, governance and institutional coverage together accounted for about 63 percent of the growth of the DLRPI, and the jumps of 2019 and 2025 followed the adoption of new legal acts. The income and adaptation blocks, which depend on economic conditions and human capital, stayed below 0.35, and none of the existing policy instruments is aimed at them. Uzbekistan has built the administrative channels of digital labor relations faster than it has improved what workers earn through these channels and how they prepare for technological change.

This pattern is consistent with the international evidence. The ILO (2021) identified low pay and unpaid time as common problems of platform work, and in Uzbekistan income is also the binding constraint. The weak adaptation block fits the task view of technological change (Acemoglu & Autor, 2011; Arntz et al., 2017): with internet use close to saturation, the real loss happens between everyday digital use and the use of digital skills at work. The case also illustrates why the ILO (2013) warned against relying on one composite number. In 2025 the geometric index stood at 0.509 and an arithmetic version would have shown 0.563, yet neither value shows on its own that adaptation is too weak for a proactive profile at any level of *R*. The two-condition rule and the profile map make this visible, and the marginal effects turn it into an order of priorities.

Two methodological results matter beyond Uzbekistan. First, the calibrated threshold of 0.410 almost coincides with the normative value of 0.40, which supports the normative choice. The silhouette values below 0.5 show, however, that nine annual observations produce only a weak cluster structure, and the calibration should be repeated on regional panel data. Second, principal component analysis on the levels of short trending series assigns weight according to the shared trend rather than actual covariation. Here it reduced the weight of the trendless protection block to 0.020. Running the analysis on first differences restored the weight to 0.183 and left the ranking of years practically unchanged. This agrees with the warning of the OECD and JRC (2008) that weights are value judgments and with the call by Greco et al. (2019) to test weighting choices explicitly. Statistical offices that build composite indices from short national series are likely to face the same problem.

For the income block the results point to a specific mechanism. Tax withholding at source, introduced in 2025 for taxi aggregators, could be extended to all labor platforms and supplemented by quarterly reports on income, active hours and social tax. Linked with the Unified National Labor System, these reports would allow the Labor Relations Center under the Ministry of Poverty Reduction and Employment to calculate indicator x_{21} every quarter:

$$x_{21,q} = \frac{\mathrm{Med}\left(Y_{i,q}/T_{i,q}\right)}{M_q/T^N} \quad (15)$$

where $Y_{i,q}$ is the quarterly income of worker i, $T_{i,q}$ the worker's active hours on the platform, M_q the minimum monthly wage and T^N the standard monthly working time. A value below one means that more than half of the workers earn less per hour than the minimum wage. In that case the tripartite commission on labor and socio-economic issues would recommend a minimum rate for the given type of platform, and part of the withheld amount would be transferred automatically as social tax, which also builds the worker's insurance record. The design follows the minimum pay guarantee of Convention No. 193 (ILO, 2026) and the data-first sequence of the Estonian model (Estonian Tax and Customs Board, 2024).

The income mechanism is necessary but not sufficient. Raising income alone to 0.40 lifts the index only to 0.553, well short of 0.65, and it does nothing for the second condition of the profile rule. Adaptation needs instruments of its own, such as a register of automation risk by occupation kept by the Labor Relations Center and reskilling orders for high-risk occupations financed through the State Employment Promotion Fund. The order of steps matters too. Protection introduced without data has uncertain coverage, and data collected without protection gives workers nothing. A staged approach that starts with the reporting flow, then adds protection that does not depend on employment status, and then adds adaptation tools looks more realistic for Uzbekistan than an immediate legal presumption of employment, which would raise platform costs and could push part of platform work into the informal sector.

The study has several limitations. Seven proxy indicators stand in for fifteen, so the results describe the national labor relations system rather than platform workers themselves. The proxy for protection, the unemployment rate, follows the business cycle, which explains the low Cronbach's alpha. The 2025 values partly rest on preliminary estimates and on the 2024 wage share. Nine annual observations constrain both principal component analysis and clustering. The expert weights were set equal for lack of a panel survey, and the legal coverage index records the adoption of norms, not their enforcement. Finally, the DLRPI is a descriptive and comparative tool, and a higher value does not prove that a given policy caused the improvement.

CONCLUSION

The paper proposed the Digital Labor Relations Proactivity Index, which measures how far a labor relations system adapts in advance to new forms of employment. The index combines fifteen indicators in five blocks, uses fixed goalposts, mixed weights and geometric aggregation, and assigns reactive, transitional and proactive profiles through a two-condition rule.

Applied to Uzbekistan, the index rose from 0.119 in 2017 to 0.509 in 2025, and the country has been in the transitional profile since 2023. The growth came mainly from legal and institutional measures. Income is the main constraint, with the largest gap and the highest marginal effect, and adaptation is the second. Clustering confirmed the normative threshold of 0.40, the ranking of years held up under random weights, and weighting on first differences removed the trend bias that had pushed the weight of the protection block down to 0.020. The profile map adds a second message: since 2023 the country has had protection without matching adaptation, so further gains depend less on new legal acts than on income and skills.

For practice, the index gives government bodies one scale for setting targets and assessing results. The National Statistics Committee could add the indicators of Table 2 to a digital employment module of the labor force survey and publish x_{21} quarterly. The Ministry of Poverty Reduction and Employment could use the gap closure coefficient as an annual performance indicator. Reaching the proactive profile by 2030 requires raising income to about 0.50, protection to 0.70 and adaptation to 0.55 at the same time. Further research should compute the index directly for platform workers from survey and administrative data, build a regional panel for more reliable calibration, and estimate the

cost of policy instruments and their effect on block subindices.

REFERENCES

1. Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In O. Ashenfelter & D. Card (Eds.), *Handbook of labor economics* (Vol. 4B, pp. 1043-1171). Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5
2. Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters, 159*, 157-160. https://doi.org/10.1016/j.econlet.2017.07.001
3. Cabinet of Ministers of the Republic of Uzbekistan. (2020). *Resolution No. 806 of 23 December 2020 on approval of the regulation on the procedure for carrying out activities as a self-employed person*. https://lex.uz/docs/-5182451
4. Cazes, S., Hijzen, A., & Saint-Martin, A. (2015). *Measuring and assessing job quality: The OECD Job Quality Framework* (OECD Social, Employment and Migration Working Papers No. 174). OECD Publishing. https://doi.org/10.1787/5jrp02kjw1mr-en
5. De Stefano, V. (2016). *The rise of the "just-in-time workforce": On-demand work, crowdwork and labour protection in the "gig-economy"* (Conditions of Work and Employment Series No. 71). International Labour Office.
6. Dingel, J. I., & Neiman, B. (2020). How many jobs can be done at home? *Journal of Public Economics, 189*, 104235. https://doi.org/10.1016/j.jpubeco.2020.104235
7. Estonian Tax and Customs Board. (2024). *Automatic exchange of platform-related information (DAC7)*. https://emta.ee/en/node/382/main_chapter/44171/pdf
8. European Parliament & Council of the European Union. (2024). Directive (EU) 2024/2831 of 23 October 2024 on improving working conditions in platform work. *Official Journal of the European Union*, L series.
9. Frese, M., & Fay, D. (2001). Personal initiative: An active performance concept for work in the 21st century. *Research in Organizational Behavior, 23*, 133-187. https://doi.org/10.1016/S0191-3085(01)23005-6
10. Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254-280. https://doi.org/10.1016/j.techfore.2016.08.019
11. Fuller, B., Jr., & Marler, L. E. (2009). Change driven by nature: A meta-analytic review of the proactive personality literature. *Journal of Vocational Behavior, 75*(3), 329-345. https://doi.org/10.1016/j.jvb.2009.05.008
12. Gawer, A. (2014). Bridging differing perspectives on technological platforms: Toward an integrative framework. *Research Policy, 43*(7), 1239-1249. https://doi.org/10.1016/j.respol.2014.03.006
13. Grant, A. M., & Ashford, S. J. (2008). The dynamics of proactivity at work. *Research in Organizational Behavior, 28*, 3-34. https://doi.org/10.1016/j.riob.2008.04.002
14. Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. *Social Indicators Research, 141*(1), 61-94. https://doi.org/10.1007/s11205-017-1832-9
15. International Labour Organization. (2013). *Decent work indicators: Guidelines for producers and users of statistical and legal framework indicators* (ILO Manual, 2nd version). ILO.
16. International Labour Organization. (2018). *Resolution concerning statistics on work relationships* (Resolution I, 20th International Conference of Labour Statisticians). ILO.
17. International Labour Organization. (2021). *World employment and social outlook 2021: The role of digital labour platforms in transforming the world of work*. ILO.
18. International Labour Organization. (2026). *Convention concerning decent work in the platform economy, 2026 (No. 193)*. International Labour Conference, 114th Session.
19. Kässi, O., & Lehdonvirta, V. (2018). Online labour index: Measuring the online gig economy for policy and research. *Technological Forecasting and Social Change, 137*, 241-248.

https://doi.org/10.1016/j.techfore.2018.07.056
20. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366-410. https://doi.org/10.5465/annals.2018.0174
21. Labour Code of the Republic of Uzbekistan, No. ZRU-798 (2022). https://lex.uz/docs/-6257288
22. Meijerink, J., & Bondarouk, T. (2023). The duality of algorithmic management: Toward a research agenda on HRM algorithms, autonomy and value creation. *Human Resource Management Review, 33*(1), 100876. https://doi.org/10.1016/j.hrmr.2021.100876
23. National Statistics Committee of the Republic of Uzbekistan. (2026). *Integrated statistical information system (SIAT): Labour market, national accounts and ICT indicators* [Data set]. https://siat.stat.uz
24. OECD & European Commission Joint Research Centre. (2008). *Handbook on constructing composite indicators: Methodology and user guide*. OECD Publishing. https://doi.org/10.1787/9789264043466-en
25. Parker, S. K., Bindl, U. K., & Strauss, K. (2010). Making things happen: A model of proactive motivation. *Journal of Management, 36*(4), 827-856. https://doi.org/10.1177/0149206310363732
26. President of the Republic of Uzbekistan. (2024). *Resolution No. PQ-347 of 4 October 2024 on measures to improve state policy and increase efficiency in poverty reduction and employment*. https://lex.uz
27. Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics, 20*, 53-65. https://doi.org/10.1016/0377-0427(87)90125-7
28. Saisana, M., Saltelli, A., & Tarantola, S. (2005). Uncertainty and sensitivity analysis techniques as tools for the quality assessment of composite indicators. *Journal of the Royal Statistical Society: Series A (Statistics in Society), 168*(2), 307-323. https://doi.org/10.1111/j.1467-985X.2005.00350.x
29. Tax Committee of the Republic of Uzbekistan. (2025, July 2). *Aggregators will pay taxes for self-employed taxi drivers* [in Uzbek]. https://gov.uz/oz/soliq/news/view/65414
30. United Nations. (2024). *SDG indicator metadata: Indicator 4.4.1, proportion of youth and adults with information and communications technology (ICT) skills, by type of skill*. UN Statistics Division.
31. United Nations Development Programme. (2025). *Human development report 2025: Technical notes*. UNDP.
32. Vallas, S., & Schor, J. B. (2020). What do platforms do? Understanding the gig economy. *Annual Review of Sociology, 46*, 273-294. https://doi.org/10.1146/annurev-soc-121919-054857
33. Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work, Employment and Society, 33*(1), 56-75. https://doi.org/10.1177/0950017018785616
34. World Bank. (2020). *The human capital index 2020 update: Human capital in the time of COVID-19*. World Bank.
35. World Economic Forum. (2025). *The future of jobs report 2025*. WEF.