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AI-Driven Management as a Future Form of Management: How Realistic Is It in Developing Countries?

Yusupov Ulug'bek Shukrullaevich,
PhD, Associate ProfessorInnovative Management Department,
Tashkent State University of Economics
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Abstract Background. AI is starting to do some of the work of managers. It plans shifts, checks job applications and decides who gets a loan. Most research on this comes from rich countries. We know much less about developing countries.
Aim. This report asks: How realistic is AI-driven management in developing countries? It argues that AI-assisted management is realistic now, but fully AI-driven management is not realistic for most developing countries in the next ten years.
Method. The report uses secondary data. It runs a statistical analysis of the IMF AI Preparedness Index for 165 countries, matched with World Bank data on income (GDP per person) for 159 of them. It uses an ANOVA test, a Kruskal–Wallis test, correlation, simple regression and Wilcoxon tests. Uzbekistan and Kenya are used as short case studies.
Results. AI preparedness is very different between country groups. Advanced economies score 0.70 on average, emerging markets 0.47 and low-income countries 0.33 ($p < 0.001$). Income alone explains 77% of the differences between countries ($r = 0.88$). Digital infrastructure is the biggest gap. In low-income countries it is only 35% of the advanced-economy level, and it is the weakest of the four areas in 57% of developing countries. Some countries, such as Rwanda, India and Kenya, score higher than their income predicts. Uzbekistan has no overall IMF score because some of its data is missing, but its available scores are above what its income predicts.
Conclusion. Money and infrastructure decide most of a country's AI readiness. Good policy helps, but only a little. For most developing countries, the realistic future is a mix: AI helps managers with some tasks, and people still make the main decisions.
Keywords: artificial intelligence, AI-driven management, developing countries, AI Preparedness Index, digital divide, Uzbekistan

1. Introduction

1.1 Background

For a long time, management was only a human job. Managers planned work, organised people, gave orders and checked results. Computers only stored the data.
Today this is changing. In 2025, 88% of companies in a large McKinsey survey said they used AI in at least one part of their business. One year earlier the number was 78% (McKinsey, 2025). Many companies are also testing "AI agents." These are programs that can plan and do several steps of a task by themselves.
In this report, AI-driven management means using AI to make or control management decisions. It can be weak or strong:

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• **AI-assisted management:** AI gives advice, and a human decides. For example, AI predicts sales, and the manager orders stock.

• **Fully AI-driven management:** AI decides and controls with very little human input. For example, a delivery app gives each driver jobs, sets the pay and rates the driver.

1.2 Literature review

The research on this topic falls into four groups.

AI as a management tool. Davenport and Ronanki (2018) studied 152 company AI projects. They found that big, ambitious projects failed more often than small projects that improved one business process. Agrawal, Gans and Goldfarb (2018) explain why. AI makes prediction cheap, but managers still need human judgement to decide what to do with a prediction. Raisch and Krakowski (2021) add a warning. Companies can use AI to replace people (automation) or to work with people (augmentation). Going too far in either direction causes problems.

AI as a boss. Kellogg, Valentine and Christin (2020) reviewed research on "algorithms at work." They showed that algorithms can direct workers, evaluate them and discipline them (Kellogg et al., 2020). Wood et al. (2019) studied online gig workers in Southeast Asia and Sub-Saharan Africa, so their study is about developing countries. Algorithmic control gave workers freedom and flexibility. But it also led to low pay, long and irregular hours, and exhaustion (Wood et al., 2019).

AI and productivity. Brynjolfsson, Li and Raymond (2025) studied 5,179 customer-support workers. An AI assistant raised productivity by 14% on average and by 34% for new, less-skilled workers (Brynjolfsson et al., 2025). So AI helps most where workers have less experience.

How new technology spreads between countries. Rogers (2003) showed that people adopt a new technology faster when it is easy to use and fits their situation. Comin and Mestieri (2018) studied 200 years of technology data. They found that new technologies now arrive in poor countries almost as fast as in rich ones, but poor countries use them much less intensively (Comin & Mestieri, 2018). The IMF expects the same with AI. About 60% of jobs in advanced economies are exposed to AI, compared with about 40% in emerging markets and 26% in low-income countries. The IMF says developing countries should first invest in digital infrastructure and digital skills (Cazzaniga et al., 2024).

1.3 Research gap

Most studies above are about rich countries, or they are about one sector such as gig platforms. Few studies use numbers from many countries to ask whether developing countries are ready for AI-driven management, or what holds them back the most. This report tries to fill part of that gap.

1.4 Research question and hypotheses

The main research question is:

How realistic is AI-driven management as a future form of management in developing countries?

The report tests three hypotheses:

• **H1:** AI preparedness is different in advanced, emerging and low-income economies.

• **H2:** A country's income (GDP per person) is strongly linked to its AI preparedness.

• **H3:** Digital infrastructure is the biggest gap for developing countries, bigger than skills, innovation or regulation.

The report's argument (thesis) is: AI-assisted management is realistic now in developing countries, but fully AI-driven management is not realistic for most of them in the next ten years. The main reason is weak foundations, especially digital infrastructure, and not a lack of interest.

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1.5 Structure

Section 2 explains the data and tests. Section 3 gives the results. Section 4 discusses what the results mean and answers counter-arguments. Section 5 concludes.

2. Methods

2.1 Research design

This is a quantitative, cross-country study using secondary data. "Secondary data" means data that other organisations collected. No new survey was done. Two short country cases (Uzbekistan and Kenya) are added to show what the numbers look like in real life.

2.2 Data

AI Preparedness Index (AIPI), IMF, 2023. The IMF built this index to measure how ready a country is to use AI (IMF, 2024). It has four parts (called "pillars"). Each pillar has a score from 0 to 0.25, and the total score is from 0 to 1.

Pillar	What it measures (simple words)
Digital infrastructure	Internet, mobile networks, online services
Human capital and labour market	Education, digital skills, how easily workers can change jobs
Innovation and economic integration	Research, new businesses, trade and investment
Regulation and ethics	Quality of laws and rules, rule of law, rules for digital business

The IMF puts every country into one of three groups: advanced economies (AE), emerging market economies (EM) and low-income countries (LIC). In this report, "developing countries" means EM and LIC together.

The IMF website could not be reached directly, so the data was taken from a public copy of the IMF dataset (mrdeecy, n.d.). To check it, the scores of 10 countries were compared with the scores the IMF published (for example Singapore 0.80, USA 0.77, India 0.49, Kenya 0.45). All 10 matched.

GDP per person, World Bank, 2023. GDP (in current US dollars) and population for 2023 come from the World Bank's World Development Indicators, through the open mirror at DataHub (DataHub GDP; DataHub population). GDP per person = GDP ÷ population. The same year (2023) is used as the AIPI.

Final sample. The dataset has 174 economies. 165 have a full AIPI score. The other 9, including Uzbekistan, miss at least one pillar. Of the 165, 159 also have GDP data. These 159 are used for the income tests.

2.3 Statistical tests

All tests use a significance level of 0.05. This means a result is called "significant" if there is less than a 5% chance it happened by luck. The analysis was done in Python 3 with the pandas and SciPy libraries.

Hypothesis	Test	What the test does (simple words)
H1: groups are different	One-way ANOVA and Kruskal–Wallis test, then Mann–Whitney tests for each pair of groups	Checks if the average scores of the three groups are really different. Kruskal–Wallis is a safer version that does not need normal data.
H1: size of	Eta squared (η^2)	Shows how much of the variation is explained by the

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Hypothesis	Test	What the test does (simple words)
the difference		group (0 = none, 1 = all)
H2: income and AI preparedness	Pearson and Spearman correlation; simple linear regression of AIPI on the natural log of GDP per person	Shows how strongly income and AIPI move together, and how much AIPI rises when income doubles
H2: over- and under-performers	Residuals from the regression	Residual = actual score − score predicted from income. Positive = the country does better than its income suggests.
H3: biggest gap	Pillar ratio and Wilcoxon signed-rank test	For each developing country, each pillar is shown as a % of the advanced-economy average. The Wilcoxon test checks if the infrastructure % is lower than the other pillars.

The natural log of GDP is used because income differences between countries are very large (from about $200 to over $100,000 per person). The log makes a doubling of income count the same at every level.

2.4 Other sources

The case studies and the discussion use reports from the World Bank, ITU, Oxford Insights, Microsoft and McKinsey, plus peer-reviewed journal articles. Official sources are used first. News articles are only used when the original report could not be opened, and this is said in the text.

2.5 Limitations

Correlation is not causation. The tests show that income and AI preparedness go together. They do not prove that income causes preparedness.

One year only. The data is from 2023. AI is changing fast.

Readiness is not the same as use. The AIPI measures whether a country is ready for AI, not how much companies really use AI in management.

Missing countries. Uzbekistan has no full AIPI score, so it is studied pillar by pillar.

Wide groups. "Emerging markets" includes both China and very small economies, so averages hide differences.

3. Results

This section first gives the statistical results for each hypothesis. Then it shows two country cases.

3.1 Overview of the data

Across 165 countries, the average AIPI score is 0.48 (lowest 0.18 in the Central African Republic, highest 0.80 in Singapore). Scores are very different between the three IMF groups.

Table 1. AIPI scores by country group (2023)

Group	Countries	Average	Median	Standard deviation	Lowest	Highest
Advanced economies (AE)	36	0.70	0.71	0.06	0.58	0.80
Emerging markets (EM)	78	0.47	0.48	0.09	0.25	0.64

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Group	Countries	Average	Median	Standard deviation	Lowest	Highest
Low-income countries (LIC)	51	0.33	0.33	0.07	0.18	0.48

The best low-income country (Kenya, 0.45) still scores lower than the weakest advanced economy (Croatia and Greece, 0.58).

3.2 H1: Are the groups really different?

Yes. The one-way ANOVA test shows a very strong difference between the groups: $F(2, 162) = 243.7$, $p < 0.001$. The Kruskal–Wallis test gives the same answer: $H = 115.3$, $p < 0.001$. Mann–Whitney tests show that each pair of groups is different (AE vs EM, EM vs LIC, AE vs LIC; all $p < 0.001$).

The effect size is large: $\eta^2 = 0.75$. This means the country group alone explains **75%** of the variation in AI preparedness.

H1 is supported.

3.3 H2: Is income linked to AI preparedness?

Yes, very strongly. For 159 countries, the correlation between AIPI and the log of GDP per person is $r = 0.88$ (Spearman $\rho = 0.88$, $p < 0.001$). The regression gives:

$AIPI = -0.338 + 0.092 \times \ln(\text{GDP per person})$

$R^2 = 0.77$, so income explains 77% of the differences in AI preparedness. The slope (0.092, standard error 0.004) means that when GDP per person doubles, the AIPI score rises by about 0.06 points. The gap between the average low-income country (0.33) and the average advanced economy (0.70) is 0.37 points. That is about the same as doubling income six times.

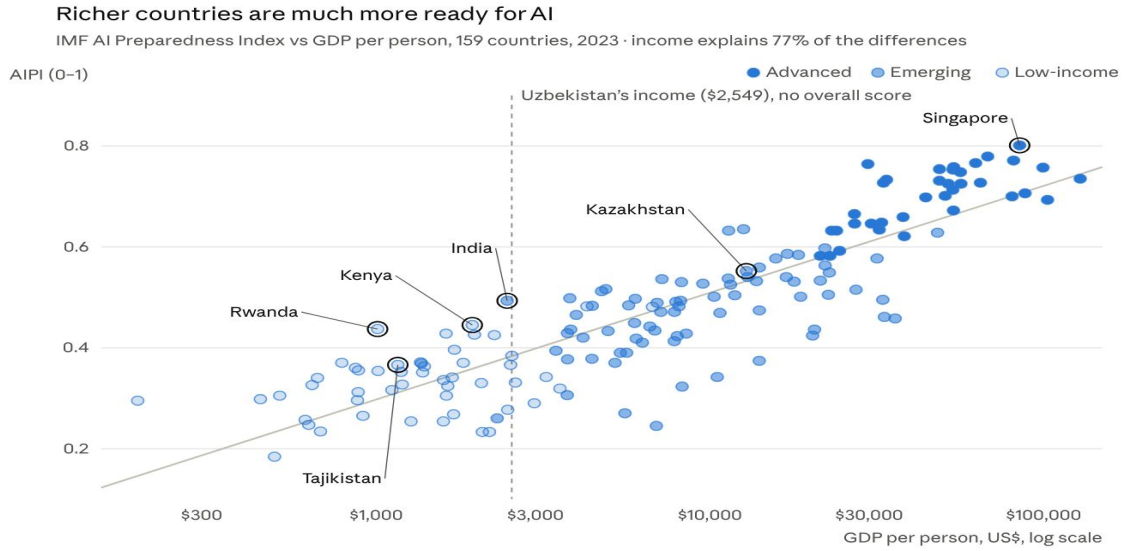


Figure 1. IMF AI Preparedness Index 2023 and World Bank GDP per person 2023 · 159 countries · line = regression fit

Some developing countries do better than their income predicts. The residual shows by how much.

Table 2. Developing countries that do better or worse than their income predicts

Better than predicted	Residual	Worse than predicted	Residual

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Better than predicted	Residual	Worse than predicted	Residual
Burundi	+0.15	Libya	−0.23
Rwanda	+0.14	Iraq	−0.19
India	+0.11	Saint Vincent and the Grenadines	−0.17
Malaysia	+0.11	Bahamas	−0.17
China	+0.11	Gabon	−0.17
Liberia	+0.10	Saint Lucia	−0.17
Kenya	+0.09		

Uzbekistan's neighbours are close to the line: Kazakhstan +0.02, Tajikistan +0.06 and Kyrgyzstan +0.07. The best over-performers gain about 0.10–0.15 points. That is useful, but it is less than half of the 0.37-point gap between low-income and advanced economies.

H2 is supported.

3.4 H3: Is digital infrastructure the biggest gap?

Yes. In low-income countries, the average digital infrastructure score is only **35%** of the advanced-economy average. The other pillars are higher: regulation 42%, human capital 55% and innovation 59%. In emerging markets, the pattern is similar but smaller.

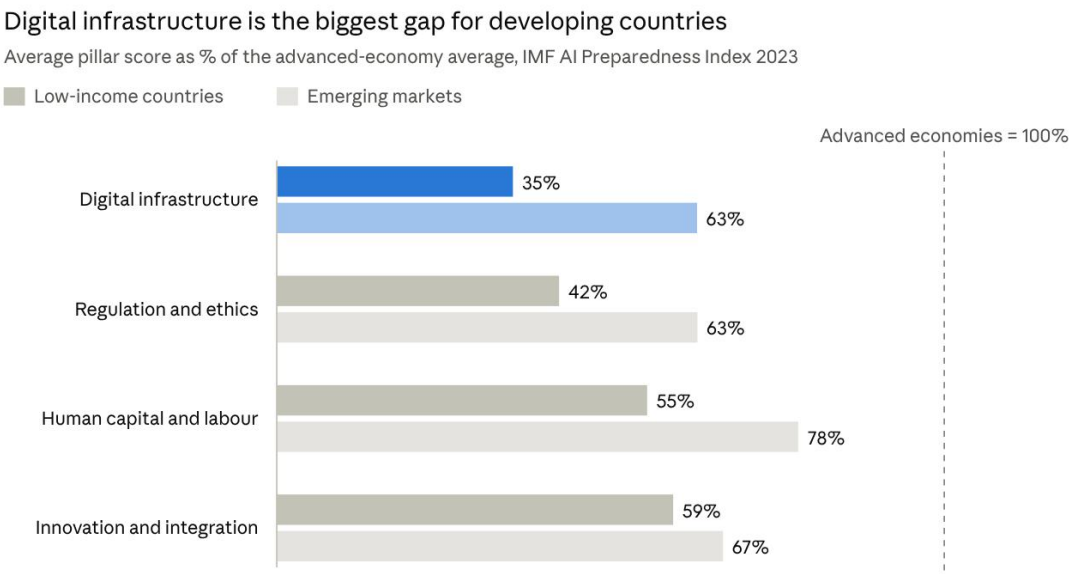


Figure 2. IMF AI Preparedness Index 2023, pillar averages by IMF country group (up to 39 AE, 79 EM and 56 LIC countries per pillar)

The same result appears country by country. For the 129 developing countries with all four pillars, the median infrastructure score is 50% of the advanced-economy level. This is lower than regulation (57%), innovation (65%) and human capital (72%). Wilcoxon signed-rank tests show these differences are significant (infrastructure vs regulation $p = 0.004$; vs innovation and vs human capital, both $p < 0.001$).

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Digital infrastructure is the weakest pillar in 73 of 129 developing countries (57%). In low-income countries, it is the weakest pillar in 39 of 51 (76%).

H3 is supported.

Other data agree. Only 27% of people in low-income countries use the internet, compared with 93% in high-income countries. Fewer than 5% of people in low-income countries have basic digital skills, compared with 66% in high-income countries. High-income countries also hold 77% of the world's data-centre capacity (World Bank, 2025b).

3.5 Readiness and real use

The AIPI measures readiness, so it is useful to check real use too. Microsoft found that in late 2025, 24.7% of working-age people in the Global North used generative AI tools, compared with 14.1% in the Global South. The gap grew during 2025, from 9.8 to 10.6 percentage points (Microsoft, 2026). Even in rich countries, real value is rare. Only about 6% of companies in McKinsey's survey get large profits from AI (McKinsey, 2025).

3.6 Case study 1: Uzbekistan

Uzbekistan is not in Figure 1, because the IMF data has no innovation score for it, so no overall score can be calculated. This missing data is itself a finding: it is hard to manage with AI when basic data is not collected. Its three other pillar scores can still be compared.

Table 3. Uzbekistan's IMF pillar scores compared with its income level

Pillar (max 0.25)	Uzbekistan	Predicted from its income	Low-income average	Emerging-market average
Digital infrastructure	0.107	0.081	0.062	0.111
Human capital and labour	0.130	0.105	0.090	0.127
Regulation and ethics	0.105	0.096	0.080	0.119
Innovation and integration	missing	0.101	0.097	0.109

Uzbekistan scores above what its income ($2,549 per person) predicts on all three pillars. It is close to the emerging-market average, even though the IMF counts it as a low-income country.

Other sources show the same picture. Uzbekistan adopted an AI strategy to 2030 in October 2024 (Gov.uz, 2024). In 2026, it set a goal of training 5 million people in AI by 2030 and opening more than 15 AI labs (Gov.uz, 2026). Internet use grew from 76.6% of people in 2021 to 94.2% in 2025 (Stat.uz, 2025). Uzbekistan's rank in the Oxford Insights Government AI Readiness Index rose from 87th in 2023 to 62nd in 2025 (Gov.uz, 2025). But the Oxford scores also show where it is weak.

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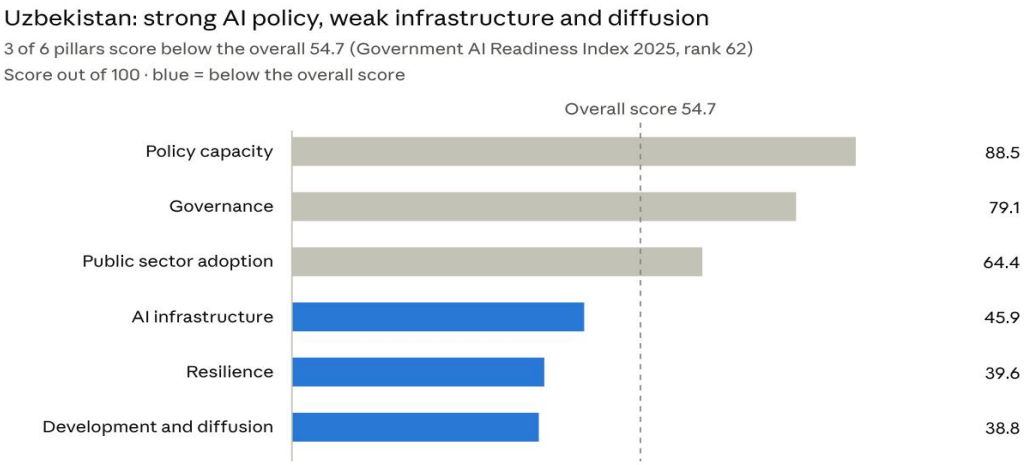


Figure 3. Oxford Insights, Government AI Readiness Index 2025, as reported by Trend (5 January 2026) · 6 pillars

The government side (policy and governance) is strong. AI infrastructure, real use in the economy (development and diffusion) and resilience are all below 50. This matches the IMF result: the foundations are the weak point.

3.7 Case study 2: Kenya

Kenya scores 0.445 on the AIPI, about 0.09 higher than its income predicts. AI has entered Kenyan management mainly through finance. Mobile money (M-Pesa) has created years of digital payment data. A Central Bank of Kenya survey in March 2025 found that half of lenders did not use AI yet. Of those that did, 65% used it for credit scoring (Business Daily, 2025).

Table 4. Use of AI for credit scoring among Kenyan lenders (news report of the CBK survey)

Type of lender	Uses AI for credit scoring
Digital credit providers	80%
Microfinance banks	75%
Commercial banks	45%

Source: TechTrends Kenya (2025). The central bank still describes most Kenyan banks as "AI-immature" (The Star, 2025). AI makes one type of decision (small loans), but people still run the banks.

3.8 Summary of results

Hypothesis	Result	Key number
H1: groups differ	Supported	$F = 243.7$, $p < 0.001$, $\eta^2 = 0.75$
H2: income linked to readiness	Supported	$r = 0.88$, $R^2 = 0.77$
H3: infrastructure is the biggest gap	Supported	LIC infrastructure = 35% of AE level; weakest pillar in 57% of developing countries

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4. Discussion

4.1 What the results mean

1. Money and infrastructure decide most of AI readiness. Income explains 77% of the differences between countries. This means a poor country cannot simply "decide" to manage with AI. Comin and Mestieri (2018) found the same pattern for older technologies: new tools arrive in poor countries quickly, but they are used much less. Our results suggest AI is following this path.

2. Good policy helps, but only a little. Rwanda, India and Kenya score 0.09–0.14 points higher than their income predicts. Uzbekistan also does better than its income on every pillar we can measure. So national effort matters. But even the best over-performers close less than half of the 0.37-point gap to advanced economies. Policy can speed things up. It cannot replace infrastructure and income.

3. The weakest link is digital infrastructure. In low-income countries it is only 35% of the advanced-economy level, and it is the weakest pillar in three out of four of them. This matters for management. AI that plans shifts, tracks stock or checks performance needs workers and managers to be online all day. Where most people are offline, this kind of AI cannot work.

4. Writing an AI plan is easier than building strong institutions. Uzbekistan scores 88.5 on AI policy capacity in the Oxford index. But in the IMF data, the regulation and ethics pillar (which measures general quality of laws and rule of law) is only 42% of the advanced level in low-income countries. A government can write an AI strategy in one year. Building trusted courts, data protection and clear rules takes much longer, and AI-driven management needs these rules to be fair.

5. AI enters management one decision at a time. Kenya shows this clearly. AI did not take over Kenyan banks. It took over one decision: who gets a small loan. This decision suits AI because it happens millions of times, has a clear result (the loan is paid back or not) and already has digital data from mobile money. Strategy, hiring senior staff and negotiation stay with people.

Together, these points support the thesis. AI-assisted management is realistic now in sectors and countries with good infrastructure. Fully AI-driven management is not realistic for most developing countries in the next ten years.

4.2 Counter-arguments and answers

"Developing countries can leapfrog." Kenya skipped bank branches and went straight to mobile money. Why not skip old management and go straight to AI?

Answer: Leapfrogging works when the new technology needs less infrastructure than the old one. Mobile phones needed less than landlines. AI is the opposite. It needs more: constant internet, clean data, computing power and skilled staff. In Kenya, AI credit scoring came only after mobile money had produced years of digital data.

"Cheap cloud tools and 'small AI' solve the problem." The World Bank shows that simple AI tools that run on ordinary phones are spreading (World Bank, 2025a).

Answer: This is partly true. Small AI makes AI-assisted work possible for many more firms, for example a shop owner who uses a phone app to plan stock. But running a whole organisation with AI needs connected systems and data across all departments. The infrastructure gap in Figure 2 is exactly this kind of gap.

"Developing countries have young workers who learn fast." Uzbekistan's median age is 27 (DataReportal, 2026), and AI helps new workers most (Brynjolfsson et al., 2025).

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Answer: This is a real advantage. But young workers only gain if they are online and have digital skills. In low-income countries, fewer than 5% of people have basic digital skills. Also, the Brynjolfsson study shows AI as a helper for workers, not as their manager.

"Many companies already use AI." McKinsey says 88% of companies use AI.

Answer: Using a chatbot to write an email is not AI-driven management. Only about 6% of companies get large profits from AI, and over half report at least one problem caused by AI (IDM, 2025).

4.3 Risks

Even where AI-driven management is possible, it can be harmful. Wood et al. (2019) found that gig workers in Africa and Asia who are managed by algorithms often have low pay, long hours and exhaustion. Kellogg et al. (2020) describe how algorithms can be used for surveillance and control. In many developing countries, labour law and data protection are weaker, so workers have less protection. AI trained mostly on English data from rich countries may also make unfair decisions about local people. Keeping a human in the loop is therefore good management, not a sign of being behind.

4.4 When does AI-driven management become realistic?

Based on the results, AI-driven management becomes realistic in a country, sector or company when:

1. Most workers are online every day.
2. The main business data is digital, not on paper.
3. The decision happens often and has a clear result (for example loans, deliveries, call routing).
4. Managers and staff have enough digital skills to check AI results.
5. Clear rules exist on who is responsible when AI makes a mistake.

Today, banking, telecoms, e-commerce and logistics in middle-income countries meet many of these conditions. Agriculture, small family businesses and most public services in low-income countries do not.

4.5 Recommendations

For managers

- Start with one frequent, data-rich decision, such as sales forecasting or customer-service routing.
- Make records digital first. AI with bad data gives confident but wrong answers.
- Use AI to support new staff, where the benefit is largest. Keep experienced managers responsible for final decisions.
- Make a clear rule for when a human must check an AI decision, especially in hiring, firing and lending.

For governments

- Put digital infrastructure at the centre of AI policy. The data shows this is the biggest gap.
- Fill data gaps. Uzbekistan has no overall IMF score because some of its data is missing.
- Update labour and data-protection laws for algorithmic management, including a right to ask for a human review.
- Support cheap AI tools in local languages.

4.6 Ideas for future research

This study used country-level data. Future studies could survey managers inside companies in Uzbekistan or Kenya, to see how AI changes daily decisions. They could also repeat the analysis with newer AIPI data to see if the gap is closing.

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5. Conclusion

This report asked: How realistic is AI-driven management in developing countries? The answer is: realistic in parts, but not as a whole, at least for the next ten years.

The statistical analysis of 165 countries gives three clear results. First, AI readiness is very different between rich and poor countries ($p < 0.001$), and the country group explains 75% of the differences. Second, income explains 77% of a country's AI readiness. Third, digital infrastructure is the biggest gap. In low-income countries, it is only about one third of the advanced-economy level.

This means AI-assisted management is already happening where the basics exist, as in Kenya's lending sector. Fully AI-driven management, where algorithms plan, control and judge a whole organisation, is not realistic for most developing countries yet. Their infrastructure, data and institutions are not ready. Good policy, as in Rwanda, India, Kenya and Uzbekistan, can help a country do better than its income suggests. But policy alone cannot close the gap.

The realistic future is a mix. People keep the main decisions and the responsibility. AI takes over small, frequent, data-rich tasks step by step. Countries and companies that first build digital infrastructure, digital records, skills and fair rules will move fastest. Those that try to copy AI-driven management from rich countries without these basics will spend a lot and gain little.

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29. Appendix: How to repeat the analysis
30. Download the AIPI file (aipidata.xlsx) and the World Bank GDP and population files from the links above.

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31. Keep the 2023 values. Divide GDP by population to get GDP per person.
32. Join the files using the three-letter country code (for example UZB, KEN).
33. In Excel, SPSS or Python, run: averages by group, ANOVA, correlation between AIPI and LN(GDP per person), and a simple linear regression.
34. You should get F ≈ 243.7, r ≈ 0.88 and slope ≈ 0.092. The cleaned data file is attached to this report as aipi_gdp_2023.csv.