The Impact of Ai-Driven Administrative Automation on Instructional Leadership Capacity and Operational Efficiency in Educational Institutions

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***Abstract*—In school and colleges, some AI tools are being used to reduce the burden of administration and there is limited awareness of how this can boost administrative leadership for learning. In this study, the relationship between AI-driven administrative automation (AIAA) and operational efficiency (OE) as well as instructional leadership capacity (ILC) is tested through a structural model with administrative time reallocation (ATR) as an intervening variable and digital and AI readiness (DR) as a moderating variable. The model, based on Job Demands–Resources model and Technology-Acceptance model, is estimated using an illustrative simulated dataset of 412 school leaders and higher-education leaders with covariance-based SEM. The measurement model has good levels of reliability and validity (CFI = 0.982 and RMSEA = 0.029). The effects of automation on operational efficiency (β = 0.517) and time reallocation (β = 0.298) are strong and moderate, respectively. Time reallocation is the primary pathway by which automation affects instructional leadership (β = 0.403) and accounts for approximately 50% of the total effect of automation. The time-reallocation effect difference between low and high-readiness leaders is more than 3-fold larger in readiness. Leaders were able to save a total of 8.2 administrative hours per week but reinvested only 43.7% in teaching. The results indicate that Artificial Intelligence inputs for leadership must be supplemented with preparations and leaders' readiness as well as dedicated protection of free time. With simulated data, the results are for demonstrating the analytical process and have to be validated using primary data.**

***Index Terms*—Artificial Intelligence, Administrative Automation, Instructional Leadership, Operational Efficiency, Educational Leadership, Structural Equation Modeling**

I. INTRODUCTION

1.1 Background

Leaders of schools and colleges devote a significant portion of their working week to official duties instead of to the teaching and learning. In the time use studies of principals, it is observed that in their roles, administrative and organizational management work consumes more time compared to various instructional tasks routinely (Horng et al., 2010; Sebastian et al., 2018). However, evidence from over 40 years shows that instructional leadership is the most predictive of student outcomes when it comes to leadership (Hallinger, 2011; Robinson et al., 2008; Grissom et al., 2021).

The tension is of long duration. Leaders are expected to monitor classes, support staff, and assess learning and use evidence to inform them of what needs to be done, including taking responsibility for timetables, attendance return, admission, orders, compliance reports and parent letters. Grissom et al. (2015) reported that principals who lacked time management skills had greater time allocated to administration and were more likely to report high levels of job stress, indicating that time may be a limiting factor in how principals practiced leadership.

The possible scope of what can be automated in institutional administration has been reshaped by the advent of artificial intelligence (AI). Previous rule-based approaches used to convert documents to digital format, while present AI systems can categorize and redirect correspondence, prepare timetables, predict enrollment and turnout, identify learners in danger and even summarize documents in natural language (Holmes et al., 2019; Chen et al., 2020). Since the end of 2022, the availability of large language models

(LLMs) has expanded this to tasks such as drafting and summarising, for which the leader would have to make their own time.

AI is now expected to get the job done for policy bodies by decreasing administrative workload. According to UNESCO policy guidance for policy makers (Miao et al., 2021), automation for administrative work is a key application of AI in education, as is the U.S. Department of Education (2023) where AI holds the promise of freeing up time for educators while maintaining them in the loop. Yet controlled trials across other industries indicate tangible benefits, such as productivity enhancements and increased completion rates for tasks involving the use of generative AI, particularly for less experienced employees (Noy & Zhang, 2023; Brynjolfsson et al., 2025).

1.2 Problem statement

The promise is that the automation provides leaders with time and that time is reinvested in instructional leadership. Both links are not guaranteed. New needs, over-control of the AI systems, and even more administration can devour freed time (Selwyn, 2019; Williamson & Eynon, 2020). Literature reviews identify that although most of the studies of AI in education focus on learners and teaching applications, AI in education administration or institutional, and administrators are largely under-researched (Zawacki-Richter et al., 2019).

This means that institutions are purchasing AI administrative tools without proof on three questions: Do the tools save the leaders' time and lead to greater instructional leadership capacity, and do the operational-efficiency benefits promised by vendors become real?

1.3 Research objectives

1. To measure the extent of AI-driven administrative automation (AIAA) in schools and higher-education institutions.
2. To examine the effect of AIAA on operational efficiency (OE).
3. To examine the effect of AIAA on instructional leadership capacity (ILC), directly and through administrative time reallocation (ATR).
4. To test whether leaders' digital and AI readiness (DR) strengthens the effect of automation on time reallocation.
5. To compare these relationships between school and higher-education settings.

1.4 Research questions

RQ1. To what extent does AIAA improve operational efficiency in educational institutions?

RQ2. Does AIAA increase the time leaders reallocate from administration to instructional work?

RQ3. Does administrative time reallocation mediate the relationship between AIAA and instructional leadership capacity?

RQ4. Does digital and AI readiness moderate the effect of AIAA on time reallocation?

1.5 Significance of the study

The study has three contributions. It is a theoretical model which combines the Job Demands–Resources model (Bakker & Demerouti, 2007) with instructional leadership theory (Hallinger & Murphy, 1985) to begin to understand how automation might evolve leadership theory, instead of simply taking its assumptions as granted. As for the methodological issues, it suggests and examines a structural equation model that contains a mediation path and an interaction term. In practical terms, it provides a foundation for leadership and policy makers to evaluate AI investments against leadership for learning, as well as cost and speed.

II. LITERATURE REVIEW

2.1 Instructional leadership and the problem of time

Instructional leadership is the work of the leader that is directly related to the quality of teaching and learning. Hallinger and Murphy (1985) defined it based on three aspects: formation of the school mission, administration of the instructional programme and provision of a positive learning climate. Their Principal Instructional Management Rating Scale (PIMRS) was adopted as the most popular measure available in the field (Hallinger, 2011).

It's backed by evidence. During a search of 27 studies, Robinson et al. (2008) concluded that on average, instructional leadership was three to four times as powerful in its impact on student outcomes as transformational leadership. The single most powerful

effect was that of leading teacher learning. In their own research, Leithwood et al. (2020) confirmed that leaders' effectiveness in improving teaching is primarily about their impact on staff motivation, capacity and working conditions. Grissom et al. (2021) did a synthesis of 20 years of literature and found that effective principals' impact on students' learning is roughly as large as an effective teacher's impact, but widespread across a school.

The issue is the amount of time. Horng et al. (2010) shadowed principals and identified that administration and organisation management were taking much of the time in the day compared to day-to-day instruction. Sebastian et al. (2018) found clear patterns of principal practice and discovered that instruction focused approached were a minority of principal practice. Neumerski (2013) stated that research had studied the job of instructional leaders more than how they integrate into their roles.

This paper thus sees instructional leadership capacity (ILC) as the IL's actual pedagogical capacity to implement the PIMRS dimensions – observing and coaching teachers, use of assessment data, leading professional learning and protecting instructional time. Capacity is largely a function of skill and time and attention.

2.2 AI-driven administrative automation in education

Examples of AI use for education can be typically classified as 3 types: Learner facing, Teacher facing, and System facing (Holmes et al., 2019). System facing group includes Administrative Automation. It includes:

- Communications: drafting, translating and routing letters, newsletters and parent messages.
- Scheduling: constraint-based timetabling, substitution cover and room allocation.
- Records: automated attendance capture, data cleaning and student information management.
- Reporting and compliance: generating statutory returns, dashboards and inspection evidence.
- Admissions and finance: application screening, fee reconciliation and procurement workflows.
- Prediction: early-warning systems that flag students at risk of absence or dropout.

The use of AI in education is older than that in tutoring systems and is found in administration, but is also less researched than tutor systems, as noted by Chen et al. (2020). In a review of 146 studies that address the use of AI in higher education, Zawacki-Richter et al. (2019) noted that topics related with institutional and administrative services were only addressed by a minority of studies, and that little critical thinking had been done about educators' roles.

The ability of generative AI has increased adoption by many degrees. An analysis of reports from a nationally representative sample of principals (2023-24) found that almost 60 percent report using artificial intelligence (AI) in their work, with most commonly using it to help draft communications, and only 18 percent say they have guidance provided in their school or district on AI use (Kaufman et al., 2025). Principals cite influences on adoption which include lack of professional development (72%), data-privacy concerns (70%) and uncertainty about how AI could support their work (70%) (Kaufman et al., 2025). A 2025 Gallup–Walton Family Foundation survey of teachers who use AI weekly reported that they believe using AI saves them 5.9 hours each week, with administrative tasks coming up as the most common cited area (Gallup & Walton Family Foundation, 2025).

2.3 Operational efficiency

Operational efficiency (OE) is the ratio of institutional outputs to the time, cost and effort needed to generate these outputs. In the education sector, it applies to processing speed (admission, fee collection), accuracy of records, and timeliness of reports as well as the cost of administrative staffing. Davenport and Ronanki (2018) split business AI applications into "cognitive engagement", "cognitive insight", and "process automation", finding that process automation offers the surest short-term efficiency benefits. Similarly, sectoral syntheses project benefits from public service improvements, but with caveats about data quality and implementations (Dwivedi et al., 2021).

There are empirical findings that like language tasks involve a productivity effect. Noy and Zhang (2023) demonstrated how professionals who leverage ChatGPT can more quickly write and have their work evaluated as higher quality, by 40%. Brynjolfsson et al. (2025) estimated an average productivity increase of 14%, specifically focussed on less-skilled (novice) customer-support agents. That's a job description for a lot of school and college administration.

2.4 Theoretical framework

Three perspectives ground the model.

Job demands–resources (JD-R) theory. The demands Bakker and Demerouti (2007) suggest include that every job has demands that draw on resources and energy supporting goal attainment. Administrative load is an old job demand – old problem – for educational leaders. AI automation can serve as a job asset, by offloading the demands and freeing up time and attention. JD-R assumes that resources will allow for core, meaningful, work; for leaders, instructional work.

Technology acceptance (TAM/UTAUT). According to the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), perceived usefulness of a technology, perceived ease of use and facilitating conditions are the bases on which benefits are obtained from a technology. In this study these conditions are captured by digital and AI readiness (DR): the leader's AI literacy, institutional infrastructure and support. The benefits from a specific degree of automation should be enhanced by readiness.

Levels of automation. Information acquisition, information analysis, decision selection and action can all be automated, as demonstrated by Parasuraman et al. (2000). According to their framework, the downside to automation of the higher levels of decisions is that people's situation awareness is degraded. As it concerns education, this means one thing: routine information and actions must be automated; pedagogical decisions and personnel decisions belong to people (U.S. Department of Education, 2023).

Distributed leadership. Spillane (2006) contends that the practice of leadership is distributed in various ways both within individuals and among instruments. AI systems are part of that spread and shift the nature of the sharing of workload within leadership, administration, and teaching.

2.5 Critical perspectives

The literature also points out concerns about not allowing pedagogy to be neglected by the use of the automated tools. Selwyn (2019) contends that using education technology can often lead to additional monitoring and maintenance requirements. Williamson and Eynon (2020) warn of the commercial interests and data-driven governance which may reinforce accountability working in education when using AI. Time saved can be virtually used by new reporting requirements, by reviewing the AI outputs or by dealing with reporting obligations with regards to privacy of data (Miao et al., 2021). The question then of whether or not freed time is used to teach more is an empirical one.

2.6 Research gap

Four gaps emerge. First, empirical studies on the role of AI in education typically address the learner and teacher participants and not the administrative tasks of leadership (Zawacki-Richter et al., 2019). Second, adoption surveys report on uses and not the impacts on leadership practice (Kaufman et al., 2025). Third, the author knows of no research that models time reallocation as a mechanism of linking automation and instructional leadership. Fourth, readiness has been so far only considered as boundary condition which has not been tested in this context.

2.7 Conceptual model and hypotheses

Drawing on JD-R and technology-acceptance theory, the study proposes the following hypotheses:

H1. AIAA has a positive effect on operational efficiency.

H2. AIAA has a positive effect on administrative time reallocation.

H3. Administrative time reallocation has a positive effect on instructional leadership capacity.

H4. AIAA has a positive direct effect on instructional leadership capacity.

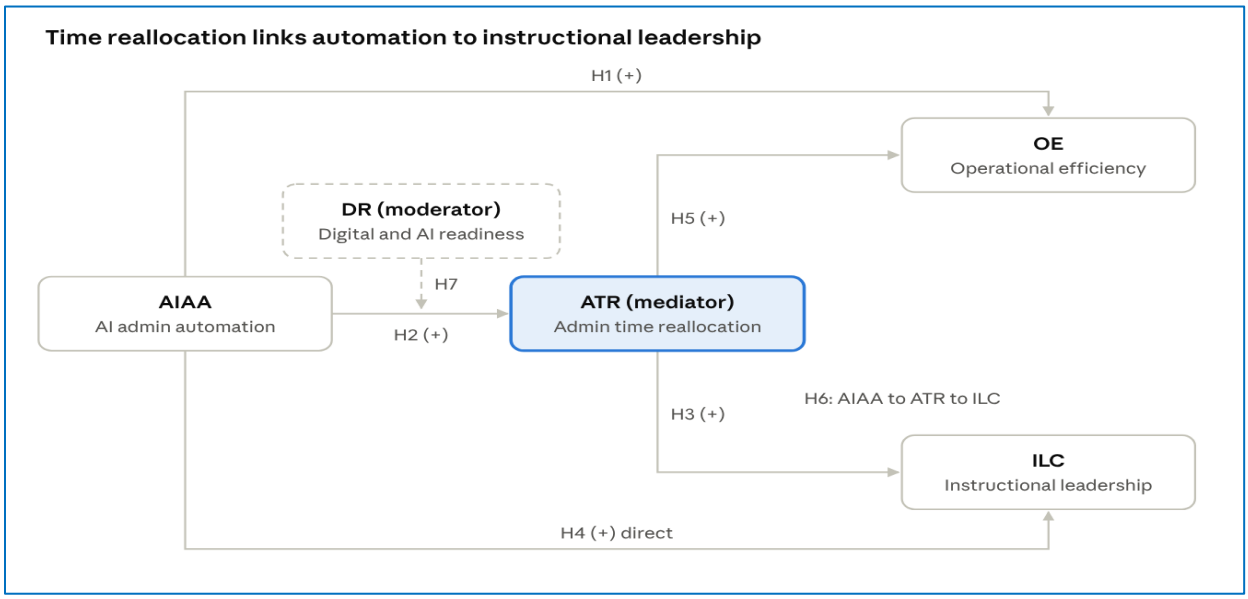
H5. Administrative time reallocation has a positive effect on operational efficiency.

H6. Administrative time reallocation mediates the effect of AIAA on instructional leadership capacity.

H7. Digital and AI readiness positively moderates the effect of AIAA on time reallocation, such that the effect is stronger when readiness is high.

Figure 1 shows the conceptual model.

Figure 1: Conceptual Model and Hypotheses (H1–H7)



Note. Automation is expected to raise efficiency directly (H1) and to reach instructional leadership both directly (H4) and through reallocated time (H2, H3, H6), with readiness moderating the automation-to-time link (H7).

III. RESEARCH METHODOLOGY

3.1 Research philosophy and design

The perspective taken in the study is the post-positivist stance and quantitative, cross-sectional survey method. Covariance-based structural equation modelling (CB-SEM) is used to test the relationships among latent constructs, essentially following the two-step procedure of Anderson and Gerbing (1988): validation of the measurement model followed by the estimation of the structural model. CB-SEM is appropriate for the purposes of this study because it examines a model that is theory based and provides global fit (Kline, 2016).

3.2 Population and sampling

Academic leaders from schools and Higher-Education Institutions (HEIs) who have implemented at least one AI-powered administrative system for at least one academic year are targeted. The principals, academic coordinator and vice-principal of the schools are the school respondents. HEI respondents include deans or directors, heads of department and registrars or administrative heads.

The sampling design is stratified purposive sampling with the strata being the institution type (school or HEI). The minimum sample was determined using two guidelines: ten cases or more per estimated structural path, and an a-priori power analysis for small to medium effects ($f^2 = 0.05$, $\alpha = .05$, and power = .80). When $N \geq 300$ both criteria are satisfied. The analytical sample ($N = 412$) comprises 241 school leaders and 171 HEI leaders.

3.3 Instrument

Five constructs were measured using a structured questionnaire on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The material is modified, restated and reused from existing sources for use in AI-assisted management. The second section measured self-reported weekly time spent on 5 groups of administrative tasks and instructional leadership, prior to and after implementing AI.

Table 1: Measurement Constructs, Items and Sources

Construct	Code	Items	Sample item	Adapted from
AI-driven administrative automation	AIAA	5	"AI tools now complete most routine correspondence in my office."	Venkatesh et al. (2003); Holmes et al. (2019)

Administrative time reallocation	ATR	4	"Automation has freed time that I now spend on teaching and learning."	Horng et al. (2010); Grissom et al. (2015)
Instructional leadership capacity	ILC	6	"I regularly observe classes and give teachers structured feedback."	Hallinger & Murphy (1985), PIMRS
Operational efficiency	OE	5	"Administrative processes are completed faster and with fewer errors."	Davenport & Ronanki (2018)
Digital and AI readiness	DR	4	"I have the skills to judge when an AI output needs correcting."	Davis (1989); Venkatesh et al. (2003)

Note. All items rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

This instrument will be content validated by a panel of educational leadership and educational technology experts and then, a pilot test will be conducted with approximately 30 leaders who are excluded from the main study. Institutional type, size of institution and leader years of experience are control variables.

3.4 Data collection procedure

The survey will be e-administered via Professional Associations and Institutional networks. Common method bias remedies are based on Podsakoff et al. (2003) – anonymity pledged, separate sections of predictor and outcome items, and neutral wording of items.

3.5 Data analysis plan

Analysis proceeds in five stages:

- Screening and descriptives: missing data, normality (skewness and kurtosis within ±2), and construct means and correlations.
- Measurement model (CFA): standardised loadings (≥ 0.60), Cronbach's α and composite reliability (CR ≥ 0.70), average variance extracted (AVE ≥ 0.50), Fornell–Larcker criterion (Fornell & Larcker, 1981) and HTMT ratios (< 0.85; Henseler et al., 2015). Model fit uses χ^2/df (< 3), CFI and TLI (≥ 0.95), RMSEA (≤ 0.06) and SRMR (≤ 0.08), following Hu and Bentler (1999).
- Common method bias: Harman's single-factor test and full-collinearity VIFs (< 3.3; Kock, 2015).
- Structural model: standardised path coefficients, R^2, and indirect effects tested with 1,000 bias-uncorrected percentile bootstrap resamples (Preacher & Hayes, 2008; Zhao et al., 2010).
- Moderation and group comparison: the AIAA × DR interaction is tested with standardised composite scores and a product term, with simple slopes at ±1 SD. School and HEI groups are estimated separately and compared.

Analyses were run in Python 3.13 using semopy 2.3 for SEM and statsmodels for regression.

3.6 Ethical considerations

In the case of conducting primary data collection in the research, institutional ethics approval, informed consent, voluntary participation and the right to withdraw would be required. All responses are anonymous; none are collected at the student level. Information is kept on encrypted hard drives and there is no reporting of individual data.

3.7 Simulated data used in this version

The dataset was created as follows: 412 cases were simulated using computer simulation (with a fixed random seed) from a population with measurements reported according to a feasible measurement error and minor cross-loadings and a small method factor were introduced that reflected the hypotheses. It is made to illustrate the entire analytical process and the form of the report.

IV. DATA ANALYSIS

All results in this section are computed on the simulated dataset described in Section 3.7.

4.1 Sample profile

Table 2: Respondent Profile (N = 412)

Characteristic	Category	n	%
Institution type	School	241	58.5
	Higher-education institution	171	41.5
Role (school)	Principal	116	28.2
	Vice-principal	86	20.9
	Academic coordinator	39	9.5
Role (HEI)	Head of department	89	21.6
	Dean / Director	48	11.7

	Registrar / Administrative head	34	8.3
Institution size (students)	Under 500	148	35.9
	500–1,500	165	40.0
	Over 1,500	99	24.0
Leadership experience	Mean 10.6 years (SD 5.6)		

4.2 Descriptive statistics and correlations

All construct means lie slightly above the midpoint of the scale (3.40-3.42). Skewness ranges from −0.27 to −0.13, and kurtosis ranges from −0.72 to −0.39: these are well within the limits of plus or minus 2 and so maximum-likelihood estimation is appropriate. There is a strong positive correlation with operational efficiency (r = .52) and a strong positive correlation with time reallocation (r = .39) rather than with automation (r = .25), a first step to mediation, but instructional leadership capacity correlates more closely with reallocation of time, than with automation.

Table 3: Means, Standard Deviations and Composite Correlations

Construct	M	SD	Skew	Kurtosis	AIAA	ATR	ILC	OE	DR
AIAA	3.40	0.87	−0.27	−0.42	1				
ATR	3.41	0.93	−0.20	−0.69	.36	1			
ILC	3.40	0.88	−0.22	−0.56	.25	.39	1		
OE	3.40	0.91	−0.13	−0.72	.52	.36	.26	1	
DR	3.42	0.89	−0.24	−0.39	.28	.39	.21	.25	1

Note. All correlations significant at $p < .001$.

4.3 Measurement model

The five-factor CFA fits the data well: $\chi^2(242) = 324.06$, $\chi^2/df = 1.34$, CFI = 0.982, TLI = 0.980, RMSEA = 0.029, SRMR = 0.038. Every index meets the Hu and Bentler (1999) thresholds.

All 24 standardised loadings exceed 0.60 (range 0.647–0.815). Cronbach's α (0.842–0.879) and composite reliability (0.843–0.880) exceed 0.70, and every AVE exceeds 0.50, establishing internal consistency and convergent validity.

Table 4: Reliability and Convergent Validity

Construct	Items	Loading range	Cronbach's α	CR	AVE
AI-driven administrative automation (AIAA)	5	0.692–0.795	0.859	0.861	0.554
Administrative time reallocation (ATR)	4	0.713–0.815	0.854	0.856	0.598
Instructional leadership capacity (ILC)	6	0.697–0.795	0.879	0.880	0.551
Operational efficiency (OE)	5	0.647–0.773	0.858	0.859	0.550
Digital and AI readiness (DR)	4	0.694–0.795	0.842	0.843	0.574

4.4 Discriminant validity

The square root of each construct's AVE (diagonal) exceeds its correlations with every other construct, satisfying the Fornell–Larcker criterion. All HTMT ratios fall between 0.240 and 0.604, below the conservative 0.85 cut-off.

Table 5: Fornell–Larcker Criterion (Below Diagonal) and HTMT Ratios (Above Diagonal)

	AIAA	ATR	ILC	OE	DR
AIAA	0.744	0.425	0.282	0.604	0.330
ATR	0.417	0.773	0.454	0.421	0.455
ILC	0.284	0.450	0.742	0.302	0.240
OE	0.602	0.420	0.300	0.742	0.297
DR	0.328	0.452	0.241	0.306	0.758

Note. Bold diagonal = √AVE. Below diagonal = latent correlations from the CFA.

4.5 Common method bias

A single unrotated factor explains 30.4% of total variance, below the 50% threshold. Full-collinearity VIFs range from 1.22 to 1.47, below Kock's (2015) cut-off of 3.3. Common method variance is therefore unlikely to bias the results.

4.6 Structural model fit

The structural model retains good fit: $\chi^2(245) = 327.04$, $\chi^2/df = 1.33$, CFI = 0.982, TLI = 0.980, RMSEA = 0.029. The model explains 28.7% of the variance in time reallocation, 40.3% in operational efficiency and 21.9% in instructional leadership capacity.

V. RESULTS AND FINDINGS

5.1 Hypothesis testing

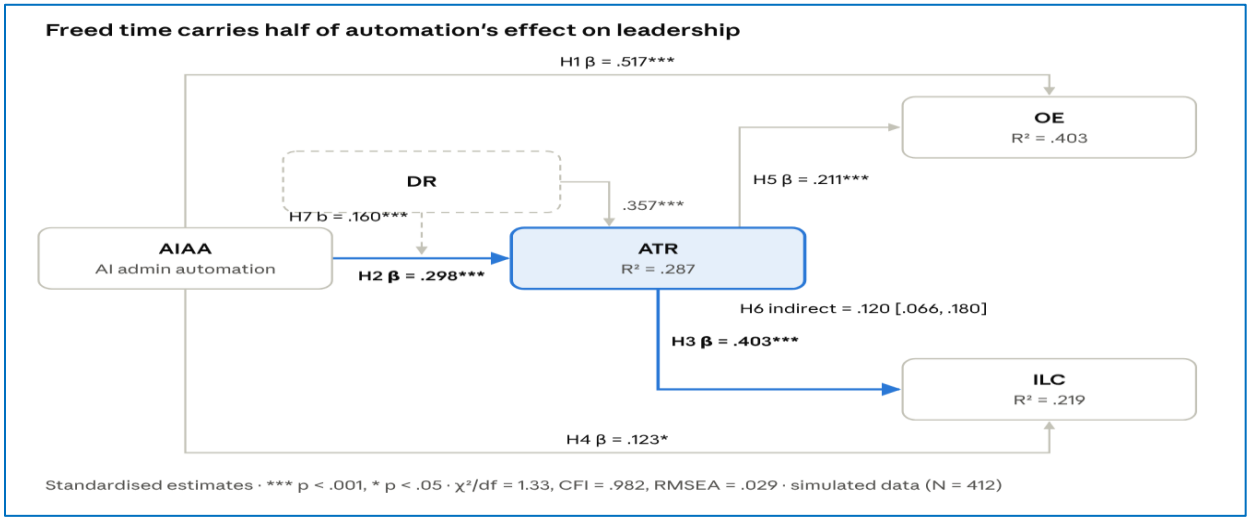
All seven hypotheses are supported. Automation has its largest effect on operational efficiency (β = 0.517) and a moderate effect on time reallocation (β = 0.298). Time reallocation, in turn, is the strongest predictor of instructional leadership capacity (β = 0.403), while the direct effect of automation on capacity is small (β = 0.123). Figure 2 shows the estimated model.

Table 6: Structural Path Estimates

Hypothesis	Path	β	SE	z	p	95% bootstrap CI	Decision
H1	AIAA → OE	0.517	0.060	8.50	< .001	[0.402, 0.619]	Supported
H2	AIAA → ATR	0.298	0.054	5.23	< .001	[0.185, 0.403]	Supported
H3	ATR → ILC	0.403	0.064	6.40	< .001	[0.292, 0.507]	Supported
H4	AIAA → ILC	0.123	0.056	2.11	.035	[0.014, 0.236]	Supported (weak)
H5	ATR → OE	0.211	0.057	3.84	< .001	[0.096, 0.321]	Supported
—	DR → ATR	0.357	0.059	6.10	< .001	—	Covariate

Note. Standardised coefficients. CIs from 1,000 percentile bootstrap resample of the full SEM.

Figure 2: Estimated Structural Model, Simulated Data (N = 412)



Note. The highlighted route, automation to time reallocation to instructional leadership, carries roughly half of automation's total effect on leadership capacity.

5.2 Mediation analysis

The combined impact of automation on instructional leadership is about half the impact of automation on leadership through time reallocation. An indirect effect was also significant (0.120, bootstrap interval does not contain zero) and the direct effect was significant as well, meaning the effects were partially mediated (H6 was supported, VAF = 49.3%). The indirect path, although significant, is small (VAF = 10.8%) as automation enhances efficiency, largely directly.

Table 7: Direct, Indirect and Total Effects of AIAA

Outcome	Direct effect [95% CI]	Indirect via ATR [95% CI]	Total effect	VAF	Mediation type
ILC	0.123 [0.014, 0.236]	0.120 [0.066, 0.180]	0.243	49.3%	Partial
OE	0.517 [0.402, 0.619]	0.063 [0.025, 0.110]	0.580	10.8%	Partial (weak)

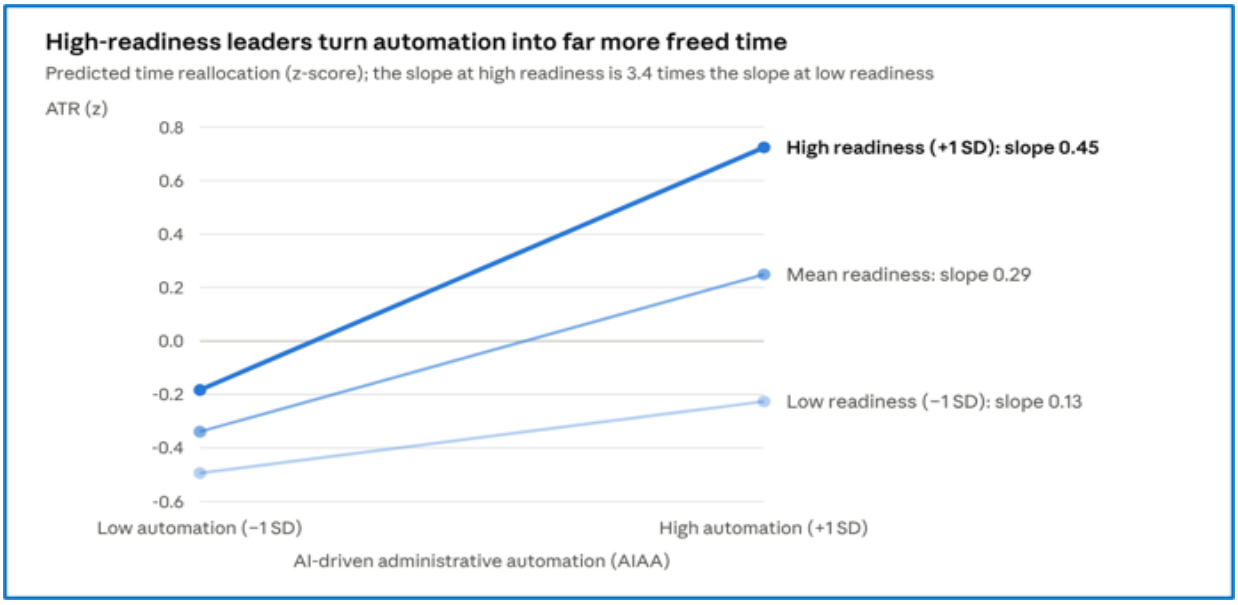
Note. VAF = variance accounted for = indirect ÷ total effect.

5.3 Moderating role of digital and AI readiness

Readiness strengthens the effect of automation on time reallocation (H7 supported). The interaction term is positive and significant (b = 0.160, t = 3.69, p < .001, 95% CI [0.075, 0.245]). It adds 2.5% of explained variance ($f^2 = 0.033$, a small effect; Cohen, 1988).

Simple-slope analysis shows that the effect of automation on reallocated time is more than three times larger for high-readiness leaders (b = 0.454 at +1 SD) than for low-readiness leaders (b = 0.134 at −1 SD). At the mean, the slope is 0.294. All three slopes are significant (Figure 3).

Figure 3: Simple Slopes of AIAA on ATR at Low, Mean and High Digital and AI Readiness (Simulated Data, N = 412)



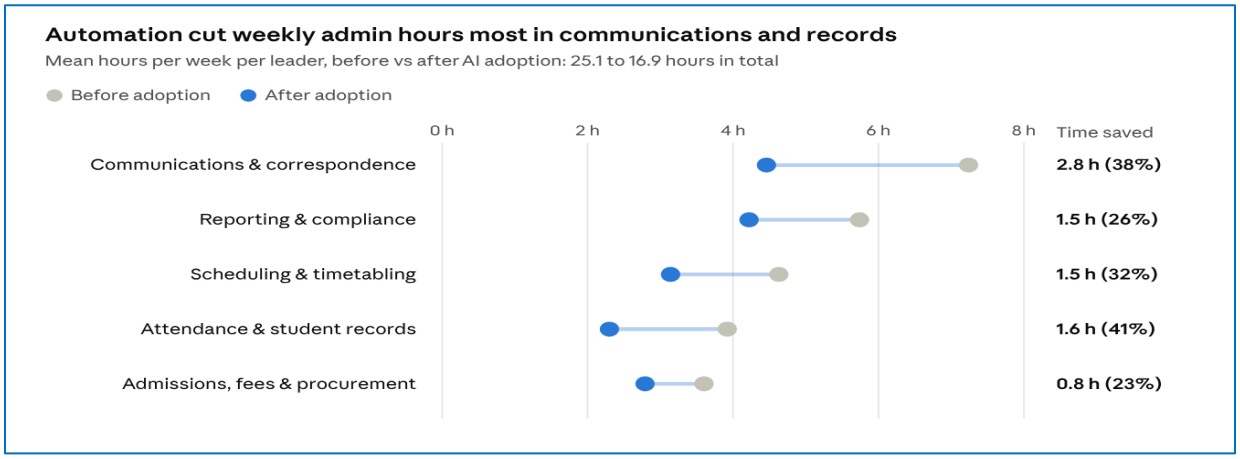
Note. At low readiness, more automation barely moves reallocated time; at high readiness, the same increase produces a steep rise.

5.4 Time-use outcomes

Respondents reported spending 25.1 hours per week on the five administrative task groups before adoption and 16.9 hours after, a saving of 8.2 hours per week (32.7%), t(411) = 49.97, p < .001. The largest proportional savings were in attendance and records (41.2%) and communications (38.4%); the smallest were in admissions, fees and procurement (22.5%), where workflows involve more human approval steps (Figure 4).

Time on instructional leadership rose from 9.8 to 13.3 hours per week (+3.6 hours; Cohen's d = 1.84). However, only 43.7% of the freed administrative time was reinvested in instructional work. The remaining 56% went elsewhere, consistent with the critical view that saved time is partly absorbed by other demands (Selwyn, 2019).

Figure 4: Weekly Administrative Hours Before and After AI Adoption, Simulated Self-Reports (N = 412)



Note. Routine, text-heavy tasks shrink most; approval-heavy admissions and procurement work shrinks least.

5.5 School versus higher-education comparison

HEI leaders reported higher automation (M = 3.51) than school leaders (M = 3.33), t = 2.10, p = .036. Other construct means did not differ.

The groups differ in how automation reaches instructional leadership. In schools, both the direct path (β = 0.204, p = .007) and the indirect path through time reallocation are significant. In HEIs, the direct path disappears (β = −0.003, p = .975), and the effect runs entirely through reallocated time (ATR → ILC β = 0.487). A formal test of the ATR → ILC path difference was not significant (b = −0.023, p = .80), so both settings rely on time reallocation to a similar degree.

Table 8: Group-Specific Structural Paths

Path	School (n = 241) β	p	HEI (n = 171) β	p
AIAA → OE	0.515	< .001	0.555	< .001
AIAA → ATR	0.277	< .001	0.339	< .001
ATR → ILC	0.336	< .001	0.487	< .001
AIAA → ILC	0.204	.007	−0.003	.975
ATR → OE	0.186	.011	0.200	.015
DR → ATR	0.353	< .001	0.340	< .001

Note. Standardised coefficients estimated separately for each group.

5.6 Summary of findings

1. AI administrative automation produces strong operational-efficiency gains (H1).
2. Automation frees leaders' time, and that time is the main channel to stronger instructional leadership (H2, H3, H6).
3. The direct effect of automation on instructional leadership is small and, in HEIs, absent (H4).
4. Leaders with higher digital and AI readiness convert automation into reallocated time far more effectively (H7).
5. Less than half of freed administrative time is reinvested in instructional work.

V. DISCUSSION

The discussion interprets the simulated results as a worked illustration of how primary findings would be read against the literature.

6.1 Automation as an efficiency resource

The strong influence of automation on operational efficiency (H1) has confirmed evidence to show that process automation is the most reliable benefit of AI (Davenport & Ronanki, 2018). It is further corroborated by experimental evidence that AI accelerates text-heavy tasks (Noy & Zhang, 2023; Brynjolfsson et al., 2025). The profile of gains at the task level reveals interesting patterns, with the highest levels of savings for tasks that are highly repetitive and rule-bound like attendance and correspondence, but lowest savings for admission and procurement, roles that involve approvals and accountability, keeping the human factor in the loop. This is consistent with the

level of automation perspective that information stages can be automated more easily than the decision and action stages (Parasuraman et al., 2000).

6.2 Time is the mechanism, not the technology

The main finding is: Automation enhances instructional leadership primarily by freeing time (H3, H6). There is a weak direct path and it is non-existent in higher education. By itself, automation is not the ticket to become a better instructional leader and it is not what will improve a leader's instructional capacity. This is in line with a JD-R perspective: freeing up resources from administration can allow leaders to focus on their core mandate (Bakker & Demerouti, 2007). It also seeks to respond to Neumerski's (2013) appeal for more research into how leaders make time for instructional work.

The limited direct impact in schools could be due to the features of AI tools that have direct impact on teaching, such as dashboards that reveal attendance or assessment trends or trigger leadership interventions. Administrative AI in HEIs is also less associated with academics and time is the only way to make it associated with academics.

6.3 The reinvestment gap

Only 43.7% of the freed time was directed to instructional activities. This is the most practically important finding in the study, and is important in the critical scholarship. Selwyn (2019) and Williamson and Eynon (2020) state that there is a tendency for new kinds of tasks and accountability demands associated with the use of educational technology. This additional time could be used to revise AI-generated content, address data security concerns, or be consumed by other tasks. Therefore, institutions must deliberately protect reallocated time, such as through institutional observation and coaching time, if they want to use automation as a vehicle to catalyze leadership for learning.

6.4 Readiness as a multiplier

The moderation result (H7) reveals that high-readiness leaders get over three times as much reallocated time with the same level of automation. This aligns with the focus of UTAUT on facilitating conditions and findings from the surveys that not having training and guidance is a big obstacle for principals when using AI (Venkatesh et al., 2003; Kaufman et al., 2025). Where data also do agree is in the direction of that effect: Survey data indicate that educators in AI policy-posing schools report greater time savings, suggesting the same directionality (Gallup & Walton Family Foundation, 2025). Investing in tools, but not in leaders' AI literacy, is unlikely to yield results at least commensurate to the investment.

6.5 Theoretical contribution

The study builds on the broad idea of instructional leadership by adding in a mediating mechanism between the organisational technology and the leadership practice (time reallocation). It applies JD-R theory to AI as a tool in the job resource of educational leadership. It also incorporates a boundary condition from technology acceptance theory, revealing that technological readiness makes up the time usable from the potential of automation.

VII. CONCLUSION AND IMPLICATIONS

7.1 Conclusion

The current study analyzed if the Educational Institutions' techniques in Administrative Automation enhance Instructional Leadership capacity and improve the operational efficiency through Involvement of AI. An analysis of an artificial dataset with 412 school and higher education leadership participants using a structural equation model, revealed a significant increase in operational efficiency and administrative time being freed for leaders by the use of automation. It is this time freed up—not the technology per se—that is the key to better instructional leadership. This is exacerbated by leaders' readiness to use digital and AI tools, but maximising the time liberated is not always being put into teaching.

The bottom line is that while AI can free up leaders' time, this time does not necessarily translate into improved leadership for learning. The "benefit" is contingent on readiness, and upon intentional decisions regarding the use of time released.

7.2 Practical implications

For institutional leaders

- Prioritise automation of high-volume, rule-bound tasks first: correspondence, attendance and records, and timetabling.

- Protect reallocated time by scheduling fixed blocks for classroom observation, coaching and data review.
- Keep pedagogical, personnel and disciplinary judgements with humans; use AI for drafting and information handling.

For policy-makers and system leaders

- Pair funding for AI tools with funding for leaders' AI literacy and change management, since readiness multiplies returns.
- Issue clear guidance on acceptable AI use, data privacy and accountability; most leaders currently work without it (Kaufman et al., 2025).
- Evaluate AI investments against leadership-for-learning outcomes, not only cost and processing speed.

For leadership preparation programmes

- Add AI literacy, critical evaluation of AI outputs, and workflow redesign to principal and academic-leader training.

VIII. LIMITATIONS AND FUTURE SCOPE

8.1 Limitations

- Simulated data. The empirical results in this version come from a simulated dataset. They demonstrate the method but cannot be generalised to any real population until replaced with primary data.
- Cross-sectional design. Even with real data, a single survey cannot establish causal order; leaders with strong instructional focus may adopt automation more readily.
- Self-report. Time-use and leadership measures rely on self-report and recall of pre-adoption hours, which are prone to bias. Procedural and statistical checks reduce but do not remove common-method concerns.
- Moderation on composites. The interaction was tested on composite scores rather than a latent interaction model, which may slightly attenuate its estimate.
- Scope. The model does not include student outcomes, teacher perceptions or the costs of implementation.

8.2 Future scope

- Primary multi-country survey. Administer the validated instrument across national contexts to test measurement invariance and compare policy environments.
- Longitudinal and quasi-experimental designs. Track institutions before and after AI adoption, using difference-in-differences or staggered-rollout designs, to strengthen causal claims.
- Objective time-use data. Combine surveys with experience sampling, calendar data or shadowing (Horng et al., 2010) to measure reallocation directly.
- Link to student outcomes. Extend the model to test whether reallocated leadership time improves teaching quality and student achievement.
- Latent interaction and multilevel models. Use latent moderated structural equations and nest leaders within institutions and districts.
- Qualitative follow-up. Explore where the unreinvested 56% of freed time goes and which institutional practices protect it.
- Ethics and governance. Study data privacy, algorithmic bias in predictive admissions or early-warning systems, and the effect of AI governance policies on outcomes.
- Generative AI agents. Examine agentic AI systems that execute multi-step administrative workflows, and their effect on leaders' oversight burden.

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