

Article

Artificial Intelligence and Leadership Practices: Enhancing Engagement and Productivity

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Abstract

This research investigates the impact of artificial intelligence (AI) and change leadership on educator engagement and productivity within the Lebanese educational sector. This study is grounded in both social cognitive theory (SCT) and dynamic capabilities theory (DCT), and it examines how AI adoption and change leadership, together with the human-centric factor of educator engagement, influence educators' productivity in the context of a developing country. Data were collected from educators from various institutions in Lebanon. Confirmatory factor analysis (CFA) was used to verify the validity and reliability of the latent factors under consideration. The hypothesized model derived from SCT and DCT and the literature was tested with structural equation modeling (SEM). The results show that change leadership significantly improves educator engagement and productivity, highlighting its important role in supporting technological transformation in educational institutions. AI has an indirect impact on productivity through educator engagement, which acts as a key mediating factor. These findings stress the significance of promoting a human-centered approach to digital transformation in education. The research offers important insights for policymakers, educators, and institutional leaders who seek to use AI effectively, particularly in environments with limited resources.

Keywords: artificial intelligence; change leadership; employee engagement; educator productivity; structural equation modeling; social cognitive theory; dynamic capabilities theory



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1. Introduction

Since 2010, the growth of artificial intelligence (AI), driven by advances in algorithms, the availability of big data, and more affordable high-performance computing (Wamba-Taguimdje et al., 2020), has reshaped how organizations operate. In 2016 the Fourth Industrial Revolution reshaped how people live, work, and connect. This transformation introduced robotics, the Internet of Things, AI and big data in various aspects of people's life (Ghosh et al., 2018). Following such a transformation, today's markets are continuously changing expeditiously, and competition is fierce; thus, organizations are under pressure to innovate to stay ahead. Contemporary organizations need to continuously advance their information technology systems, while integrating them into their management

strategies, as customers expect high-quality standards that are intertwined with advances in technology. Additionally, as organizations are moving from employee-driven work to technology-driven operations, the demand for a digital workforce increases. Following such necessities, many universities commenced a University 4.0 open system model that encourages communication, collaboration, and innovation. Universities' shift towards the University 4.0 model to align with Industry 4.0 has changed how they teach and create knowledge to educate future employees for industry demands (Giang et al., 2021).

The existing literature on AI in education (AIED) supports that AI impacts teaching methods and learning outcomes as it changes educators' roles (Xu & Ouyang, 2022) and promotes personalized learning. Educational institutions that use AI applications to deliver educational content can improve instructional effectiveness through customization (B. George & Wooden, 2023). AI helps education by automating admin tasks, grading, assessment, and feedback. AI platforms such as Knewton, Turnitin, Grammarly, Ecree and Intelligent Tutoring Systems (ITSs) make performance evaluations easier. These platforms reduce teachers' workloads and support students better (Abbes et al., 2024). AI web-based education systems (AIWBEs) provide grading templates, instructional support, and customized content. They are useful for teachers who manage various levels of student groups. The shift to remote learning during the COVID-19 pandemic further accelerated the adoption of AI-based grading systems, helping to standardize assessments, reduce bias, and continuously improve through machine learning and clustering algorithms (Ahmad et al., 2022).

AI systems can do tasks that humans normally do, such as making decisions, recognizing speech, and spotting patterns instantly (Korteling et al., 2021). AI systems draw on many tools, including machine learning, deep learning, and natural language processing (Benbya et al., 2020; Gârdan et al., 2025; Irwanto, 2025). More sectors are adopting AI, and institutions need to provide employees with appropriate tools to achieve flexibility, as well as to remain engaged and productive so they can navigate this change effectively. This transformation improves operational efficiency by enabling employees to make meaningful contributions toward the organization's strategic objectives (Wijayati et al., 2022).

Studies have shown that organizational performance is improved with AI; it supports decision-making and helps employees exchange information and focus on their tasks (Olan et al., 2022). Additionally, AI automates activities, raises employees' job satisfaction, encourages innovation, and improves employees' flexibility (Ademola, 2024; Olan et al., 2022). Subfields such as networks, knowledge representation, genetic algorithms, and natural language processing improve human abilities and change the way work is done within the organization.

AI can also improve institutions' administration operations. For example, admissions can use chatbots to respond with automated, pre-written answers to general questions (Ahmad et al., 2022). Today, AI tools reduce the workload and allow employees to focus more on complex tasks, as they can use AI to run operational activities relatively easily. When AI tools handle inquiries, employees can spend more time on tasks that need human intelligence so that the overall service is more reliable. It is clear that AI improves education by adding hands-on learning experiences through virtual reality and 3D technology, especially in the medical education field, which use simulations for surgical and anatomy training (Zou et al., 2026). Abbes et al. (2024) found that AI-powered robots teach advanced skills while intelligent tutoring systems (ITSs) mimic instructor behavior to deliver the learning that fits each student. Accordingly, collaboration between AI and educators leads to more engaging, student-centered learning environments.

Despite this emerging body of research, the existing literature has rarely jointly investigated the relationships between AI adoption, change leadership, and educator engagement

within a single integrated model. Moreover, such relationships have rarely been investigated within the context of a developing country that is undergoing simultaneous economic and institutional crises. Lebanon offers more than a convenient example of a developing country; it represents a distinctive test case for AI adoption research precisely because its economic and institutional conditions are so severe. The national poverty rate nearly quadrupled between 2012 and 2022, from 12% to 44% (World Bank, 2024), while sustained currency devaluation has eroded public-sector wages to the point that many educators can no longer meet basic living costs. This has driven substantial emigration among experienced teaching staff, with private-schoolteacher attrition estimated above 15% in the years following the onset of the crisis (El Deeb, 2021). This trend has continued amid recurring regional conflict and institutional paralysis through 2024–2025. These conditions are not incidental background; they directly shape the infrastructural and human-resource constraints under which any AI adoption must occur, including unstable electricity, unreliable internet access, and a shrinking, increasingly inexperienced teaching workforce. Studying AI adoption and change leadership in this setting, therefore, tests whether relationships established in resource-rich contexts hold when the basic preconditions for technology adoption, stable power, connectivity, and workforce continuity are themselves in question. In this sense, Lebanon functions less as a representative sample of “developing countries” in general and more as a boundary case that reveals what AI-driven organizational change looks like under sustained institutional stress, a condition increasingly common but underexamined in the AI education literature. This study addresses that gap by testing the direct and mediated effects of AI integration, as well as change leadership, on educator productivity through the lens of dynamic capabilities theory and social cognitive theory, within this uniquely constrained setting.

2. Literature Review and Hypotheses

2.1. Artificial Intelligence in the Educational System

Since the launch of AI in 1956, various sectors have progressively adopted it as computing power developed to handle big data, and machine learning technologies have grown at a fast pace (Guan et al., 2020). The evolution of expert systems and the advancement of networks and deep learning approaches are found to be significant milestones to the AI evolution at work (Yang & Zhu, 2024). Nowadays, several governments and technology giants are interested in the capacity of AI to perform tasks which were previously performed by employees because they required cognition, learning, and problem-solving abilities.

The potential of AI to execute several functions by optimizing processes and improving productivity and decision-making capabilities requires all levels of employees to develop new skills in technology, creativity, and social interaction. Technological revolutions also affect the education sector across the world in the way teaching and learning are delivered (Limna et al., 2022). The adoption of AI in education is found to tailor instruction, simplify administrative tasks, and promote efficiency in teaching and learning. For instance, AI enables students to adapt the educational materials to their personal learning needs and demands. Data derived from several course assessments (e.g., quizzes, tests, and classroom interactions) are personalized using various AI-powered platforms (e.g., DreamBox, Knewton); thus, students are provided with individual feedback (Owan et al., 2023; Rajput, 2025). Along the same lines, ITSs (e.g., ALEKS, Carnegie Learning) provide students with immediate feedback and adjust tutorials to their learning styles. Other natural language processing tools may also support students’ development and writing skills (e.g., Grammarly, Google Cloud) and provide educators with relevant insights into students’ engagement with the course materials. Even more, the new technology is also embedded in transcription and translation applications (e.g., Otter.ai), which accommodate the needs of students with

language barriers and/or disabilities (Owan et al., 2023). Beyond these technologies, many other AI applications, such as virtual assistants, gamified learning platforms, and immersive technologies (e.g., virtual and augmented reality), develop more interactive and engaging learning environments. These tools improve students' academic learning and development of necessary skills such as collaboration, creativity, and problem-solving.

The adoption of AI in teaching and learning also enables efficiency in classroom management. For instance, educators use learning management systems (LMSs) (e.g., Blackboard and Canvas) that include AI features to deliver educational materials/content and track students' progress. LMSs can support both in-person and online teaching (Gumasing et al., 2022). Additionally, educators can automate grading with these tools (e.g., Turnitin, Grammarly), which helps educators to skim effectively through assignments, detect wrong answers, and provide prompt feedback. Grading is a time-consuming activity, and AI releases teachers from extreme workloads. As such, new technology leaves educators the time and space they need to interact more with academic life (Adiguzel et al., 2023; Owan et al., 2023). Also, the adoption of AI systems such as DeepSeek and Claude AI may help educators to deliver educational materials using natural language and to process contextual reasoning. On top of that, educational institutions that make use of predictive analytics collect data of students' attendance, participation, and achievement to monitor their progress and take effective and direct actions when necessary (Xu & Ouyang, 2022).

From the discussion above, we argue that the adoption of AI in education is revolutionizing the teaching and learning experience. It enables educators to develop flexible and inclusive learning environments, thus personalizing students' learning needs and demands. At the same time, the adoption of AI prepares students for the ever-changing requirements of today's economy. Drawing on the theory of dynamic capabilities (Teece et al., 1997), which focuses on organizations' ability to adapt and adjust their resources to keep up with fast-changing environments (Siaw & Ali, 2025), we support that educational institutions should identify their threats and opportunities, take action, and transform their organizations to stay in line with external changes. As dynamic capabilities grow with continuous knowledge acquisition, experimentation, and developments in organizational routines (Gremme & Wohlgemuth, 2017), both internal (e.g., organizational culture, leadership, decision-making) and external (e.g., new technology, institutional change) organizational variables should be considered (Kovacevic et al., 2025).

Teece (2018) defined leadership as an open, flexible cultural variable with the potential to drive innovation and develop organizational environments which benefit from new opportunities and, accordingly, adjust their processes, resources, and structure. Dynamic capabilities are increasingly important in the context of AI integration as they enable organizations to adapt and reorganize resources to respond to new technologies (Gao et al., 2025). Change leadership influences employee engagement and promotes the development of dynamic capabilities that allow organizations to grow and make full use of AI adoption.

However, the adoption of AI in education is largely dependent on actors who do not yet trust that they will benefit. Key decisions still require human intelligence. Social cognitive theory (SCT), initially developed by Bandura (1986), explains that people learn based on triadic reciprocity, which further illustrates the interaction of environmental, personal, and behavioral factors (Riley et al., 2016); therefore, one's beliefs and confidence in the adoption of AI influence their subsequent actions.

Integrating a strategic-management theory developed at the organizational level (DCT) with a psychological theory developed at the individual level (SCT) requires more than asserting that the two are compatible; it requires establishing why cross-level integration is theoretically warranted in the first place. We draw on the microfoundations literature in strategic management (Felin et al., 2012, 2015), which argues that organizational-level

constructs such as dynamic capabilities are not self-standing explanatory primitives but emerge from, and are enacted through, individual-level cognition, decisions, and interactions. On this view, an institution's capacity to sense opportunities, seize them, and reconfigure resources (DCT) is observable only through the aggregated actions and beliefs of the individuals who carry it out. This provides the theoretical warrant for linking DCT to SCT: change leadership, as an organizational-level dynamic capability, does not influence productivity directly but operates through its effects on individual educators' efficacy beliefs and behavioral engagement—the very mechanisms SCT is designed to explain. The two theories are therefore not merely juxtaposed but connected through an explicit microfoundational logic, in which SCT supplies the individual-level mechanism through which a DCT-level capability translates into observable outcomes.

Although DCT and SCT use different approaches of analysis, we theorize them as integrated rather than isolated frameworks. Specifically, we propose that change leadership functions as an organizational-level dynamic capability that shapes the environmental leg of Bandura's (1986) triadic reciprocity, i.e., by sensing the need for AI adoption, communicating a clear change vision, and reconfiguring resources and routines (DCT). In that, change leaders alter the environmental conditions educators encounter, which in turn shape educators' self-efficacy beliefs and behavioral engagement with AI (SCT). Stated as a cross-level theoretical proposition, organizational sensing and seizing capabilities (DCT) shape the contextual environment that influences educators' efficacy, beliefs, and behavioral engagement (SCT), which are subsequently translated into productivity outcomes. This theoretical bridge clarifies the reason that change leadership and AI adoption are integrated, rather than treated as additive antecedents to educators' engagement and productivity.

Hence, this study examined the effects of AI adoption and change leadership on educators' productivity, as well as the role of educators' engagement in these relationships. To this end, we used the theoretical framework of dynamic capabilities to explain how change leadership helps educational organizations adopt AI to raise educators' engagement and productivity. At the same time, we used social cognitive theory to explain the psychological and behavioral mechanisms which motivate educators to adopt AI. In this way, we seek to explain (i) the effects of AI adoption on educators' productivity, (ii) the mediating role of engagement in this relationship and (iii) the role of change leadership in both educators' productivity and engagement. The study hypotheses are developed respectively in the subsequent sections.

2.2. Impact of AI Integration on Educators' Engagement and Productivity

Employee engagement refers to the emotional connection employees develop for their job, organization, and goals, further reflecting their enthusiasm and commitment to the success of the business (Chandani et al., 2016; Rahadian Yudistira & Al Faruq Abdullah, 2024). Engaged employees are motivated to perform extra roles, often going beyond their formal job responsibilities, thus contributing to the success of their organization (Mittal et al., 2023). Educators' engagement grows significantly as job resources that support their routine tasks and activities become available, providing them with timely feedback and enabling them to learn. AI integration creates more personalized work experiences, which improve educators' engagement. It may also identify needs, give real-time feedback, and support and suggest learning opportunities. This kind of support improves student–educator relationships and engagement, leading to greater productivity (Mittal et al., 2023; Prentice et al., 2023; Wijayati et al., 2022). Additionally, educators can achieve challenging goals, deliver high-quality services, and manage complex tasks more effectively with AI. Iram et al. (2026) highlight that, while AI can improve employee productivity, it advances the skills employees need and ensures that employees are prepared for these shifts.

Employee productivity is often defined as an essential employee attribute for the efficient and effective production of high-quality outputs (Dixit & Sharma, 2021). Contemporary work environments in different sectors require employees to align rapidly with their organization's strategic goals (Waqar et al., 2024). At the same time, employees act as innovators to increase their individual performance (A. S. George, 2024). The existing literature suggests that employees who have access to workplace resources and participate in training and development programs develop skills and abilities (e.g., problem-solving, innovation, and strategic thinking) that enable them to achieve both individual and organizational goals.

The adoption of Industry 4.0 technologies, such as robots and smart machines, is found to create productive workplaces and provide employees with greater flexibility and autonomy to perform their tasks (Gabsi, 2024). These technologies simplify routine activities, sharpen precision, and optimize workflows (Arslan et al., 2022; Farooq & Sultana, 2022). For instance, AI-based automation handles repetitive tasks, reducing processing time significantly. This, in turn, allows employees to focus on more meaningful, creative, and strategic work to accomplish the goals set by their organizations (Kaur, 2024). Similarly, AI plays an important role in boosting efficiency and business intelligence (Wang et al., 2022). By automating repetitive chores, employees can focus more on creative and innovative parts of their jobs (Malik et al., 2022).

Thus, responsible AI adoption transforms teaching and learning and creates effective and efficient learning environments for both students and educators (Baig & Yadegaridehkordi, 2025). AI enables better and more direct communication channels between students and educators as it helps the latter to manage lecture schedules and appointments, reduce stress, and improve lecture delivery (Li & Jan, 2023). AI also eases research, workload management, and student evaluations, and supports the implementation of course curricula, allowing educators to perform their roles more efficiently. Based on the discussion above, we shape the following hypotheses:

H1. *AI adoption has a positive impact on educators' productivity.*

H2. *AI adoption has a positive impact on educators' engagement.*

H3. *Educator's engagement has a positive impact on educators' productivity.*

2.3. The Role of Change Leadership

Change leadership refers to various dynamic actions taken by leaders in organizations to guide and support the process of change while improving employee productivity (Engida et al., 2022). Such leadership actions aim to explain the need for change, articulate their vision and commitment, and describe how they will support, monitor, and control progress. Change leadership increases employee participation in various organizational actions while sharing relevant knowledge and developing opportunities for employee involvement. Change leadership emphasizes the roles of leadership and change agents who act in the context of top-down, episode-driven changes in organizations. Change leadership moves beyond the linear tradition of change in teams, organizations, and society as it emphasizes using its own distinct model of behavioral, spiritual, and emotional intelligence (Issah, 2018; Piwowar-Sulej & Iqbal, 2024).

Change leadership plays a central role in AI adoption across organizational settings. Van der Voet (2016) explained that effective change leadership strengthens employees' engagement to the change process by clearly communicating and encouraging participation in its implementation. Strong leadership is essential for guiding employees to overcome challenges associated with AI adoption, as it helps organizations to manage resistance

to change and foster a positive work environment. The more the leaders are engaged and involved in organizational changes, the more positively the employees respond to them (Herold et al., 2008; Iram et al., 2026). Along the same lines, leadership practices that encourage flexibility, experimentation, and responsiveness to change directly influence an organization's ability to implement and optimize AI technologies. Based on the rationale above, H4 and H5 (presented below) reflect the expected positive role of change leadership in shaping educators' engagement and productivity, respectively.

H4. *Change leadership impacts educators' engagement.*

H5. *Change leadership impacts educators' productivity.*

Based on DCT and SCT, which explain the proposed relationships among the key constructs, a conceptual framework was developed to support the impact of change leadership and AI adoption on educators' productivity, as well as the mediating role of their engagement. The conceptual framework for the structural equation model is illustrated in Figure 1.

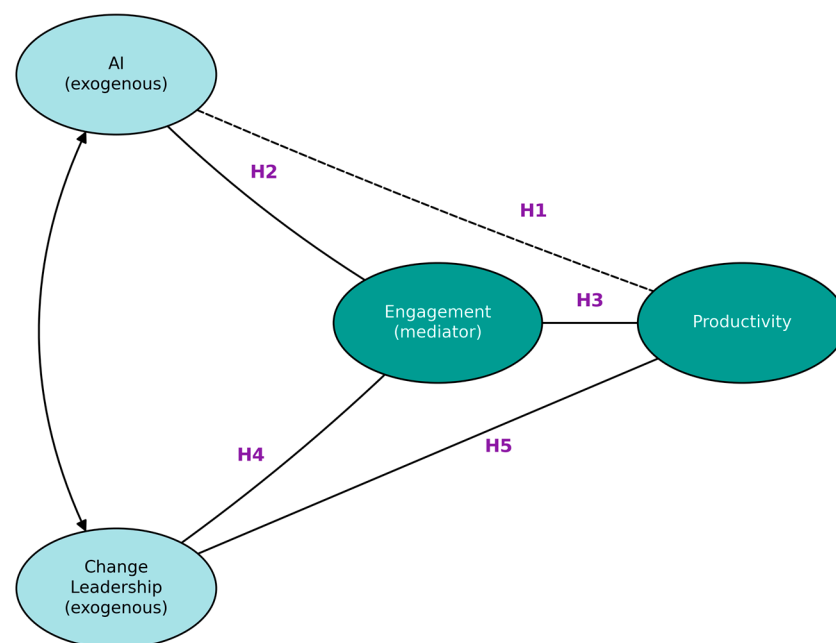


Figure 1. Conceptual framework (structural equation model). The curved arrow between change leadership and AI adoption denotes a correlational association only; straight arrows represent the structural (regression) paths that are formally tested via SEM and correspond to H1–H5.

3. Study Methodology and Methods

3.1. Sample and Procedure

A survey was created on SurveyHero, and prior to the full data collection, it was pilot tested with a selected group of educators (schoolteachers and university instructors) to gather expert feedback and information on its validity and reliability. Respondents were recruited using convenience sampling. The survey link was circulated through the authors' professional and personal networks of schoolteachers and university instructors across Lebanon, primarily via email, WhatsApp, and social media platforms, and respondents were encouraged to share the survey with eligible colleagues (a snowball element). No fixed institutional sampling frame was used, which we acknowledge as a limitation in Section 5.3; because recruitment relied on existing networks and voluntary onward sharing, the sample may over-represent educators who are more digitally connected or more open to engaging

with AI-related research, and the findings should be interpreted with this potential self-selection bias in mind. Respondents were assured that their responses would remain fully confidential, in line with data protection procedures. A total of 177 valid responses were included in the final analysis (out of 203) and were analyzed with confirmatory factor analysis (CFA) and subsequent structural equation model (SEM) analyses (Section 4). Cases with missing observations (26) were excluded from the analysis. This resulted in the removal of 13% of the initial responses. The decision to delete these cases was guided by the recommendations of Hair et al. (2019), who suggest that cases with excessive levels of missing data may be deleted, particularly when their exclusion substantially reduces the overall extent of missing data.

As the study followed a cross-sectional design, potential issues relevant to common method bias (CMB) were addressed with the use of both Harman's single-factor test and the more rigorous CFA marker-variable technique (Williams et al., 2010). An unrotated principal component analysis of all substantive indicators extracted three factors with eigenvalues greater than 1, and the first (largest) factor accounted for 51.9% of the total variance. Because this value marginally exceeds the conventional 50% threshold, Harman's test alone was inconclusive regarding the presence of CMB, underscoring the need for the more diagnostic marker-variable analysis that followed. Using educator's mental health,¹ a theoretically unrelated three-item construct, as the marker variable, a baseline CFA including the substantive factors and the marker factor (uncorrelated with the substantive constructs) showed good fit: $\chi^2(125) = 205.733$, CFI = 0.971, TLI = 0.965, RMSEA = 0.060, and SRMR = 0.041. Adding a method factor with loadings from the marker onto all freely estimated substantive indicators (Method-R model) did not significantly improve fit relative to the baseline ($\Delta\chi^2(8) = 6.38$, $p = 0.605$), indicating that the data do not require a method factor to explain the pattern of substantive relationships. Constraining these method-factor loadings to be equal across indicators (Method-C model) likewise did not significantly worsen fit relative to either the baseline model, $\Delta\chi^2(6) = 10.46$, $p = 0.107$, or the freely estimated Method-R model, $\Delta\chi^2(14) = 16.84$, $p = 0.267$. All three models showed comparable and acceptable fit (CFI = 0.970–0.971, TLI = 0.962–0.965, RMSEA = 0.060–0.063, SRMR = 0.040–0.057), with no practically meaningful change in fit as method-factor parameters were added or constrained. Taken together, these results indicate that CMB does not account for a statistically or practically significant portion of shared variance among the study's indicators; therefore, CMB does not pose a meaningful threat to the validity of the study's substantive conclusions (Table 1).

Table 1. Chi-square difference tests.

Comparison	$\Delta\chi^2$	Δdf	p -Value	Interpretation
Method-C vs. Method-R	216.193 – 199.353 = 16.84	131 – 117 = 14	0.267	Not significant
Baseline vs. Method-R	205.5733 – 199.353 = 6.38	125 – 117 = 8	0.605	Not significant
Baseline vs. Method-C	216.193 – 205.733 = 10.46	131 – 125 = 6	0.107	Not significant

3.2. Measures

All study variables were derived from the existing literature and were measured using five-point Likert scales except for the educator's engagement variable that was measured using a seven-point Likert scale (1 = Never, 2 = Almost never, 3 = Rarely, 4 = Sometimes, 5 = Often, 6 = Very often, 7 = Always). Scale reliabilities were acceptable, ranging from 0.880 to 0.969, as presented in Table 2.

Table 2. Construct items and loadings.

Latent Variable	Estimate	Std.Err	z-Value	p-Value	Std.all
Artificial Intelligence					
AI3. I can differentiate between the functions and features of AI-related tools and applications.	1				0.736
AI5. I can explain how AI applications in education offer a solution to which problem.	1.055	0.107	9.88	0.000	0.762
AI7. I can explain the AI applications used in educational services to the students.	1.305	0.115	11.315	0.000	0.878
AI8. I can choose the proper AI application for the problem encountered in education.	1.194	0.111	10.743	0.000	0.828
Productivity					
Prod4. I utilized AI-based platforms to keep my knowledge up to date with the latest teaching methods and educational tools.	1				0.832
Prod5. AI-based training tools helped me continuously improve my work-related skills.	1.170	0.070	16.800	0.000	0.971
Prod6. AI tools helped me generate creative solutions for complex teaching challenges and problems.	0.934	0.066	14.192	0.000	0.849
Engagement					
Eng2. I find the work I do in education, with the integration of AI, full of meaning and purpose.	1				0.920
Eng3. Time flies when I am working with AI tools in my educational role.	1.009	0.052	19.262	0.000	0.891
Eng4. At my job in education, I feel strong and vigorous, particularly with the support of AI.	1.022	0.050	20.295	0.000	0.908
Eng5. I am enthusiastic about my job in education, especially with AI's growing role.	1.021	0.048	21.216	0.000	0.922
Change Leadership					
CL1. The institution/supervisor developed a clear vision for what was going to be achieved through the integration of AI in our educational work unit.	1				0.911
CL2. The institution/supervisor clearly communicated to us why the adoption of AI was necessary for enhancing educational practices.	1.048	0.047	22.416	0.000	0.939
CL3. The institution/supervisor made a compelling case for the urgency of adopting AI in education before the implementation.	1.040	0.042	24.635	0.000	0.966
CL4. The institution/supervisor built a broad coalition of support for the integration of AI in our educational work unit.	1.020	0.045	22.888	0.000	0.945

Specifically, *artificial intelligence (AI) adoption* was measured using an 8-item construct developed by [Karaca et al. \(2021\)](#).

Educators' productivity was assessed with the 18-item individual work performance questionnaire (IWPQ) by [Koopmans et al. \(2012\)](#), which measures three aspects of job performance: task performance, contextual performance, and counterproductive work behavior.

Educators' engagement was measured using a 9-item construct adapted from [Schaufeli et al. \(2006\)](#), capturing the three dimensions of engagement: vigor, dedication, and absorption. Each of the dimensions was represented by three items.

Change leadership was measured using a 7-item construct developed by [Herold et al. \(2008\)](#), focusing on leadership behaviors that support organizational change.

In addition to the substantive constructs above, educators' mental health was measured with a study-specific 3-item marker scale (assessing general work-related stress and emotional strain, theoretically unrelated to the study's substantive model) that was included in the survey instrument specifically to enable the CMB marker-variable analysis.

Following the CFA results, all items with loadings below 0.7 were removed as recommended ([Hair et al., 2019](#)). The remaining items are shown along with their loadings in Table 2.

The respondents' demographic profiles for the remaining sample were divided into two groups: schoolteachers and university instructors or professors. There were 58 schoolteachers and 119 university instructors included in the study. Additionally, respondents were classified into four categories based on their experience with technology.

The Beginner group (10.81% of the sample) included respondents with limited experience who require assistance. The Intermediate group (51.80%) consisted of those who are comfortable using technology and can perform most tasks independently. The Advanced group (27.03%) included respondents with extensive experience who can troubleshoot and optimize technology usage. Finally, the Expert group (0.90%) consisted of individuals with specialized knowledge who train or support others in technology-related tasks. Given that the Expert category comprised only 0.90% of the sample, it is retained for descriptive completeness only and is not used in inferential subgroup comparisons in this study.

4. Data Analysis and Results

4.1. Confirmatory Factor Analysis: Checking Fit and Construct Reliability and Validity

Confirmatory factor analysis (CFA) was first conducted to determine the loadings on each latent component and subsequently to eliminate the items with low loadings. Using R's Lavaan package, we evaluated the construct reliability and validity of the measurement model. Table 3 presents the goodness-of-fit indices for the refined CFA four-factor model. The results indicate that the four-factor model shows a fairly good fit. The relative fit indices show acceptable model fit (CFI = 0.976, TLI = 0.970, RMSEA = 0.066, SRMR = 0.044). The normed chi-square ($=150.12/85 = 1.77$) indicates an acceptable fit (Bergh, 2015).

Table 3. Goodness-of-fit indicators for the newly adjusted model.

Test Type	Result	Cutoff Value	Interpretation
Chi-squared (χ^2)	261.1 ($p < 0.01$) ***	≥ 0.05	Significant p -value
χ^2/df	$=1.55$	< 3	Acceptable fit
RMSEA	0.079	≤ 0.08	Acceptable fit
SRMR	0.05	≤ 0.08	Good fit
CFI	0.965	≥ 0.90	Good fit
TLI	0.956	≥ 0.90	Good fit

Note: This is sensitive to sample size. The chi-square test was significant *** ($p < 0.01$); however, the chi-square statistic is sensitive to sample size. Therefore, model fit was assessed using multiple complementary goodness-of-fit indices.

Table 4 presents the construct reliability (CR) values for the latent constructs in the four-factor model. The CR values for all constructs ranged from 0.880 to 0.969, exceeding the recommended cutoff of 0.70. This indicates that all the latent constructs demonstrate high reliability.

Table 4. Construct reliability and validity tests for the final CFA model.

Latent Construct	Reliability	AVE	MSV	ASV
AI adoption	0.880	0.651	0.439	0.261
Educator's productivity	0.924	0.789	0.474	0.260
Educator's engagement	0.951	0.828	0.474	0.317
Change leadership	0.969	0.884	0.579	0.268

Table 5 also displays the average variance extracted (AVE) for each construct in the four-factor model. The AVE values ranged from 0.651 to 0.884, all exceeding the recommended threshold of 0.50, indicating strong convergent validity (Cheung et al., 2024).

Table 5. Discriminant validity test for the final CFA model (condition 2).

Latent Factor 1	Latent Factor 2	AVE 1	AVE 2	R-Squared
AI adoption	Educator's productivity	0.651	0.789	0.262
AI adoption	Educator's engagement	0.651	0.828	0.439
AI adoption	Change leadership	0.651	0.884	0.125
Educator's productivity	Educator's engagement	0.789	0.828	0.474
Educator's productivity	Change leadership	0.789	0.884	0.199
Educator's engagement	Change leadership	0.828	0.884	0.167

Discriminant validity is established when the following two conditions are met: (1) the maximum shared variance (MSV) and average shared variance (ASV) for each construct are less than the construct's AVE and (2) the square root of the AVE for each construct is greater than its correlation with other constructs (Berhanu et al., 2025). The first condition ensures that each factor shares more variance with its own indicators than with other latent factors. The MSV for each construct ranged from 0.439 to 0.579, while the ASV for each construct ranged from 0.261 to 0.317, all of which are below the typical AVE cutoff values, indicating that the first condition for discriminant validity is met. The AVE values (Table 5) for each pair of latent factors, as well as their corresponding (R^2) values, indicate that, for all latent factor pairs, the AVE values are greater than the shared variance (R-squared), thereby satisfying the second condition of discriminant validity. Overall, these findings confirm that all constructs in the four-factor model demonstrate adequate discriminant validity, as each construct is more distinct than the others.

In addition, discriminant validity was assessed using the Fornell–Larcker criterion (Fornell & Larcker, 1981), which requires the square root of each construct's AVE to exceed its correlations with all other constructs. As shown in Table 6, the square root of the AVE for each construct (AI = 0.807, Educator's productivity = 0.888, Educator's engagement = 0.910, Change leadership = 0.940) exceeded its correlations with all other constructs, confirming that discriminant validity was established across the measurement model.

Table 6. Fornell–Larcker criterion matrix.

Construct	AI	Productivity	Engagement	Change Leadership
AI	0.807			
Educator's productivity	0.512 ***	0.888		
Educator's engagement	0.662 ***	0.688 ***	0.910	
Change leadership	0.354 ***	0.446 ***	0.409 ***	0.940

Notes: *** $p < 0.001$. Diagonal values are the square root of AVE; off-diagonal values are inter-construct correlations.

Table 6 also presents the standardized correlations between the latent factors in the final CFA model. The results indicate that all correlations were positive and statistically significant at the 1% level ($p < 0.01$), showing that the constructs are theoretically related. These findings provide strong evidence of nomological validity and reveal strong positive relationships, providing initial support for the proposed hypotheses. AI was also significantly and positively correlated with educators' productivity ($r = 0.512$, $p < 0.001$), educators' engagement ($r = 0.662$, $p < 0.001$), and change leadership ($r = 0.354$, $p < 0.001$). This confirms that higher perceptions of AI integration are associated with improved educator outcomes and stronger organizational support mechanisms (Arslan et al., 2022; Olan et al., 2022; Wijayati et al., 2022). Educators' productivity was positively correlated with educators'

engagement ($r = 0.688, p < 0.001$) and change leadership ($r = 0.446, p < 0.001$), supporting the idea that these factors work together to enhance organizational performance (Dwivedi et al., 2020; Nazir & Islam, 2017). Similarly, educators' engagement showed strong positive correlations with change leadership ($r = 0.409, p < 0.001$), reinforcing the importance of organizational and interpersonal dynamics in promoting educators' engagement (Ahmed et al., 2020; Caulfield & Senger, 2017).

4.2. Measurement Invariance Test

To ensure that the measurement model functions similarly across different subgroups, a measurement invariance test was conducted. This is an important step to confirm that different groups of respondents similarly interpret the latent factors to minimize/eliminate any plausible measurement bias (Putnick & Bornstein, 2016). In this study, the sample was divided into two groups according to their professional roles: schoolteachers and university instructors. Separate CFAs were conducted for each group to evaluate the consistency of the model structure and validity across different educational contexts. Table 7 presents the results of the model fit indices and the different validity tests applied for each group. The results show that the model demonstrates an acceptable-to-good fit across both groups. While the university teachers' CFA model yielded slightly better model fit results (higher CFI/TLI values, lower RMSEA and SRMR values), the schoolteachers' CFA model also met the minimum cutoff values for acceptable model fit (SRMR < 0.08, CFI > 0.90 and TLI > 0.90). Significantly, all validity tests were satisfied for both groups. These results show that the measurement model is invariant across different educational groups, supporting the generalizability of the latent factors and their relationships in both school and university settings.

Table 7. Model fit test for the CFA model based on separate groups.

Test Type	Schoolteachers	University Teachers
Chi-squared (χ^2)	123.6 (p -value < 0.01)	137.5 (p -value < 0.01)
RMSEA	0.090	0.073
SRMR	0.077	0.042
CFI	0.939	0.973
TLI	0.924	0.966
Construct reliability test	Pass	Pass
Convergent/Discriminant/Nomological validity tests	Pass	Pass

4.3. SEM Fit

Following the validation of the measurement model, structural equation modeling (SEM) is used to examine hypothesized relationships, including direct and mediating effects. The structural equation model tested includes three key relationships: (1) the effect of change leadership on AI adoption; (2) the influence of AI and change leadership on educators' engagement; and (3) the effect of AI, engagement and change leadership on educator productivity. The first path is based on the idea that supportive change leadership practices positively influence the adoption of AI in educational settings (Teece, 2018). The second path is grounded in social cognitive theory and suggests that AI can enhance educators' engagement (Bandura, 1986). Likewise, effective change leadership is expected to play an important role in creating a collaborative and supportive learning environment. The third structural path is based on the hypothesis that AI enhances educator productivity

both directly and indirectly through engagement, change leadership practices, and the automation of redundant tasks (Iram et al., 2026; Kassa & Worku, 2025).

The goodness-of-fit and relative fit indices shown in Table 8 reveal that the structural equation model fits the data fairly well (CFI = 0.976, TLI = 0.969, RMSEA = 0.066, SRMR = 0.041), thus supporting the adequacy of the proposed structural equation model (Bergh, 2015; Zheng & Bentler, 2025).

Table 8. Goodness-of-fit indicators for the SEM.

Test Type	Result	Cutoff Value	Interpretation
Chi-squared (χ^2)	149.5 ($p < 0.01$) ***	≥ 0.05	Significant p -value
RMSEA	0.066	≤ 0.08	Good fit
SRMR	0.041	≤ 0.08	Good fit
CFI	0.976	≥ 0.90	Good fit
TLI	0.969	≥ 0.90	Good fit

Note: This is sensitive to sample size. *** $p < 0.001$.

Table 9 presents the results of the structural path coefficients. Although the existing literature supports that AI significantly affects educators' productivity, the results indicate a weak, insignificant direct effect of AI adoption on educators' productivity ($\beta = 0.071$, $p = 0.402$), thus rejecting H1. The results confirm a strong and statistically significant positive effect of AI on educators' engagement ($\beta = 0.591$, $p < 0.001$), supporting H2. This finding supports similar results obtained by Gusti et al. (2024) and Calderon Hoyos (2023). The results also indicated that educators' engagement has a strong positive and significant effect on their productivity ($\beta = 0.564$, $p = 0.000$), supporting existing work by Dwivedi et al. (2020); thus, H3 is accepted. The last two results indicate that AI indirectly impacts productivity through the engagement factor, which functions as a full mediator between the two (i.e., full mediation, since the direct AI $\rightarrow$ Productivity path is non-significant while the indirect path through engagement is significant).

Table 9. Structural path coefficients.

Hypothesized Path	Std. Est.	p -Value	Outcome
H1: AI adoption $\rightarrow$ Productivity	0.071	0.402	Insignificant direct effect (Reject H1)
H2: AI adoption $\rightarrow$ Engagement	0.591	0.000 ***	Strong, significant (Accept H2)
H3: Engagement $\rightarrow$ Productivity	0.564	0.000 ***	Strong, significant (Accept H3)
H4: Change leadership $\rightarrow$ Engagement	0.200	0.003 ***	Strong, significant (Accept H4)
H5: Change leadership $\rightarrow$ Productivity	0.190	0.000 ***	Significant direct effect (Accept H5)

Note: *** $p < 0.001$.

On the other hand, change leadership has a moderately positive significant effect on educators' engagement ($\beta = 0.200$, $p = 0.003$), supporting the strategic role of change leadership in engaging educators (Teece, 2018), and reinforcing its significant role in fostering a collaborative learning environment and confirming existing claims proposed by Caulfield and Senger (2017). Change leadership also has a significant positive effect on educator productivity ($\beta = 0.190$, $p = 0.000$). This result supports the existing literature that change leadership practices are a key factor in enhancing educator productivity (Iram et al., 2026). Thus, we may conclude that educators' engagement plays a partial mediating role between change leadership and educators' productivity.

Following Hayes's (2013) or Baron and Kenny's (1986) approach, bootstrapped bias-corrected confidence intervals (5000 resamples) indicated that the indirect effect of AI on productivity through engagement was significant (indirect effect = 0.475, 95% CI [0.285, 0.745]), as was the indirect effect of change leadership on productivity through engagement (indirect effect = 0.161, 95% CI [0.048, 0.312]). Both confidence intervals excluded zero, supporting engagement as a significant mediating mechanism for both predictors. The proportion of the total effect that was mediated was substantially larger for AI ($\approx 82\%$) than for change leadership ($\approx 37\%$), suggesting that engagement functions as a near-full mediator of AI's effect on productivity, while change leadership retains a meaningful direct effect on productivity independent of engagement.

In summary, these results imply that although change leadership and AI both have noteworthy effects on educators' engagement, educators' engagement plays an important role as a mediator between change leadership and AI adoption on one side and productivity on the other; this is reflected in the final structural model in Figure 2.

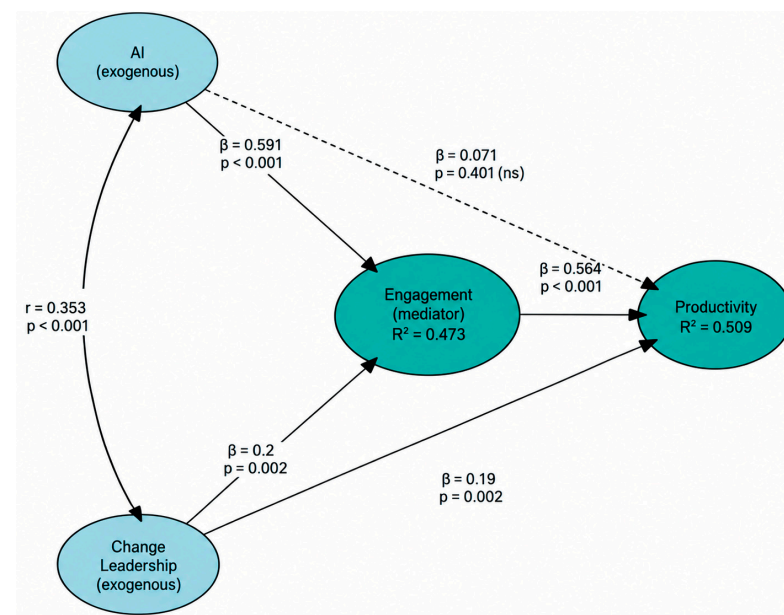


Figure 2. Structural equation model outcomes.

5. Discussion and Conclusions

The study empirically investigated the impact of artificial intelligence and change leadership on educator productivity, as well as the mediating role of their engagement, using structural equation modeling to test a theoretically grounded model. The findings provide important insights and practical implications for educational institutions aiming to integrate AI into their learning environments.

First, the study's findings highlight the critical role of change leadership in improving educator engagement and productivity, further supporting the adoption of AI within educational institutions. These findings receive significant support from the existing literature, thus providing a more thorough understanding of the importance of supportive leadership practices for the development of a collaborative and productive learning environment.

Second, the study findings suggest that AI significantly enhanced educator engagement without having a direct impact on their productivity. This further indicates the primary function of AI as an indirect driver of educators' productivity, which is achieved through their engagement. In other words, AI enhances productivity through engagement rather than having a direct effect. Educators' engagement emerged as a strong and significant mediator between AI adoption and educator productivity, confirming prior studies

and emphasizing its importance as a key predictor of performance outcomes. Additionally, change leadership was found to positively influence both educator engagement and productivity, highlighting the important role of leadership practice in supporting technological transformation and maintaining workforce motivation. As with cross-sectional studies, these relationships should be interpreted as associative rather than strictly causal, and they are discussed in detail in the subsequent sections.

5.1. Theoretical Implications

The study's contributions to the existing literature are threefold. First, this study contributes mainly to the literature on AI, leadership, and human resource management. According to DCT, Teece (2018) and Gremme and Wohlgemuth (2017) considered leadership an antecedent of organizational capabilities, whereas this study finds that change leadership should itself be considered a dynamic capability that supports organizations' readiness to adopt AI and reconfigure their functions. This research addresses a major gap by showing that change leadership has a significant impact on educator engagement and productivity while also supporting the organizational conditions necessary for AI adoption. Contemporary leadership is therefore vital to reconfiguring organizations for new technology environments.

Secondly, this study reveals that by integrating SCT with AI research, educators more readily accept and understand organizational digital transformation when newer technologies are human-centered. This means that productivity will not be improved by AI alone but it will only improve significantly when educators are progressively engaged with AI.

Thirdly, a major contribution to theory is the introduction of the conceptual framework that integrates AI adoption, which incorporates change leadership to enable human resource management capability. The framework positions educators' engagement as a key human-centered mechanism linking AI adoption and change leadership to educator productivity, and combines DCT and SCT into a single working model, as elaborated in the cross-level theoretical bridge proposed in Section 2.1.

5.2. Practical Implications

The results of this study provide multiple practical implications for both the education sector and other related services attempting to encourage AI adoption to improve productivity.

Educational leaders and policymakers should recognize the importance of how change leaders can effectively introduce and adopt AI. The strategic adoption of AI within these contexts may enhance educator engagement and improve work processes accordingly. This may ultimately contribute to higher productivity. In preparing the groundwork for educators' engagement, change leaders need to design two-way training programs. These programs should promote the effective use of AI, thus supporting educators' engagement with AI. They should also boost educator productivity. Finally, leaders in education must provide continuous support and training throughout educators' careers, especially when AI tools are upgraded.

As the context of the study is the Lebanese education sector, those who are involved in the adoption of AI in education should further consider the characteristics of this context, such as economic instability, plausible infrastructural constraints, and the emigration of skilled educators, to mention a few. For instance, in the Lebanese education sector, many institutions are struggling to adopt AI as they operate with limited and unstable electricity supply, as well as with limited Wi-Fi access. In such cases, educational leadership should prioritize low-bandwidth, offline-capable AI tools over resource-intensive platforms. To

manage such constraints effectively, educational leaders of under-resourced schools with constrained budgets may avoid costly external consultancy programs. Rather, they should participate in or attend change leadership workshops to learn and understand how to lead with low-cost peer-mentoring models. We further suggest the involvement of policymakers (e.g., the Lebanese Ministry of Education and Higher Education) in any supportive action towards the adoption of AI across both well-resourced private institutions and under-resourced public schools. These actions may range from the development of national guidelines to the subsidization of infrastructure.

5.3. Limitations and Directions for Future Research

As is common in academic research, our study presents limitations that warrant further attention. First, one of the main study limitations is the context of the analysis; data for this study were collected only from one geographical area, Lebanon, as well as only from the education sector. Future research may also focus on international environments, depart from the education sector and expand into other industries and sectors.

Second, as the study we conducted was cross-sectional, common method bias (CMB) could be a potential concern. To address this issue, we used both Harman's single-factor test and the more rigorous CFA marker-variable technique. The study findings indicate that CMB was not an issue for our study as it did not pose any meaningful threat to the study's substantive conclusions. Yet, future research may incorporate multi-source or multi-wave studies to reduce any potential limitation that is relevant to single-source, single-time-point, and self-reported data. Consistent with the limitations of cross-sectional studies, the reported relationships of our study should be interpreted as associative rather than causal. As aforementioned, longitudinal or experimental studies are further needed to establish causality with greater confidence among the pathways of AI, engagement, and productivity, as well as the pathways of change leadership, engagement, and productivity.

Although the study sample is representative, it can be characterized as a relatively small sample size ($N = 177$). In addition, as it is a convenience and non-probability sample, its statistical power and generalizability may be plausibly limited. Therefore, future research could draw on a larger, geographically diverse probability-based sample to strengthen future replication. Lastly, future research should also compare and contrast the impact of change leadership on the relationships under study against alternative leadership styles (e.g., transformational or servant leadership). This could further help to explain the role of leadership in the relationship between educator engagement and productivity.

Although measurement invariance testing confirmed that the latent constructs are interpreted equivalently by schoolteachers and university instructors (Section 4.2), we did not test whether the structural paths among these constructs (H1–H5) are of equal strength across the two subgroups. Schoolteachers and university instructors operate under different pedagogical models: one oriented toward fixed curricular content, the other toward critical, open-ended inquiry. So, it is plausible that AI adoption, change leadership, and engagement relate to productivity differently depending on the nature of the material being taught. We consider the pooled analysis presented here defensible for two reasons: first, the constructs measured describe an educator's relationship to their institution and to technology rather than to specific subject content, making them conceptually role-general; second, established measurement invariance provides a necessary, though not sufficient, condition for meaningful pooled comparison. We nonetheless recognize that a full multi-group structural comparison, testing whether path coefficients differ significantly between schoolteachers and university instructors, would offer a more rigorous test of this assumption, and we flag it as a priority for future research with samples large enough to support adequately powered multi-group SEM in each subgroup.

This study shows that AI adoption alone does not raise educator productivity; it does so only when it strengthens educator engagement, and change leadership is what makes that translation possible. For policymakers and institutional leaders, this points to concrete action rather than general encouragement. Institutions should pair any AI rollout with structured, two-way training that builds educators' confidence and sense of ownership over the tools, rather than introducing platforms such as automated grading systems, AI-assisted lesson planning, or learning-management analytics without a parallel investment in how educators are supported to use them. Leaders should expect, and plan for, a period in which engagement, not the technology itself, is the binding constraint on productivity gains, and should resource change leadership accordingly to include clear communication of why a given tool is being adopted, visible institutional commitment, and ongoing support after initial rollout, rather than a one-time training session. In the Lebanese context specifically, this means prioritizing low-bandwidth, offline-capable tools over resource-intensive platforms, and channeling limited budgets toward peer-mentoring structures rather than costly external consultancies. Taken together, these findings suggest that the practical challenge facing educational institutions is not primarily technological, but organizational, building the leadership and engagement conditions under which AI can actually be used well.

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Note

- ¹ The construct named “Educator’s mental health”, and used as a marker variable, is composed of the following three items created by Motowidlo et al. (1986): Item 1: I feel a great deal of stress because of my work in education, especially with the integration of AI. Item 2: Very few stressful situations arise in my role in education, even with the application of AI. Item 3: My work in education is extremely stressful, particularly with the increasing use of AI.

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