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# **Bridging the Gap: Applying AI and Bayesian Statistics to Traditional Educational Leadership Training**

# Acortando la brecha: aplicación de la IA y la estadística bayesiana a la formación tradicional en liderazgo educativo

**Diego Donoso**<sup>1</sup>: ECOTEC Technological University, Ecuador. <u>ddonoso@ecotec.edu.ec</u> **Ana María Gallardo:** ECOTEC Technological University, Ecuador. <u>agallardo@ecotec.edu.ec</u>

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#### Abstract:

**Introduction:** In the dynamic landscape of modern organizations, leadership is a vital competency. However, traditional uniform approaches often fail to address the diverse challenges posed by contemporary environments. Social, educational, and technological transformations, including the rise of artificial intelligence (AI), necessitate a shift toward more adaptive leadership styles. **Methodology:** This study explores situational leadership in higher education, focusing on its responsiveness to AI-driven resource management and its role in fostering professional success. Using Bayesian analysis, the study evaluates the effectiveness of project-based learning (PBL) in developing leadership qualities. Data from 404 educators across 28 institutions were analyzed, covering ten variables related to leadership and PBL. **Results:** The results offer insights into curricular development and educational strategies to equip students with essential skills for professional success. **Discussion:** Situational leadership, as developed by Hersey and Blanchard, emphasizes adapting leadership styles to follower maturity and specific situations, highlighting the need for flexibility in dynamic environments. **Conclusions:** The model's focus on follower maturity distinguishes it from static leadership models, underscoring its enduring relevance.

<sup>&</sup>lt;sup>1</sup> Corresponding author: Diego Donoso. Universidad Tecnológica ECOTEC (Ecuador).





**Keywords:** leadership; artificial intelligence; higher education; Bayesian analysis; Project-Based Learning (PBL); educational strategies; curricular development; professional success.

#### **Resumen:**

Introducción: En el dinámico panorama de las organizaciones modernas, el liderazgo es una competencia vital. Sin embargo, los enfoques tradicionales uniformes a menudo no abordan los desafíos diversos que presentan los entornos contemporáneos. Las transformaciones sociales, educativas y tecnológicas, incluyendo el auge de la inteligencia artificial (IA), requieren un cambio hacia estilos de liderazgo más adaptativos. Metodología: Este estudio explora el liderazgo situacional en la educación superior, centrándose en su capacidad de respuesta a la gestión de recursos impulsada por IA y su papel en el fomento del éxito profesional. Utilizando análisis bayesiano, el estudio evalúa la efectividad del aprendizaje basado en proyectos (PBL) en el desarrollo de cualidades de liderazgo. Se analizaron datos de 404 educadores de 28 instituciones, abarcando diez variables relacionadas con el liderazgo y PBL. Resultados: Los resultados ofrecen ideas sobre el desarrollo curricular y estrategias educativas para dotar a los estudiantes de habilidades esenciales para el éxito profesional. Discusión: El liderazgo situacional, desarrollado por Hersey y Blanchard, enfatiza la adaptación de los estilos de liderazgo a la madurez de los seguidores y situaciones específicas, destacando la necesidad de flexibilidad en entornos dinámicos. Conclusiones: El enfoque en la madurez de los seguidores distingue este modelo de los modelos de liderazgo estáticos, subrayando su relevancia duradera.

**Palabras clave:** liderazgo; inteligencia artificial; educación superior; análisis Bayesiano; Aprendizaje Basado en Proyectos (ABP); estrategias educativas; desarrollo curricular; éxito profesional.

## 1. Introduction

Leadership is a critical skill in the modern business and organizational landscape, but the traditional one-size-fits-all approach is proving insufficient in the face of diverse challenges. Social, educational, and technological changes, including the integration of artificial intelligence, require a more adaptive leadership style. This investigation explores the concept of situational leadership and its application in the university educational context, examining its adaptability to the use of artificial intelligence for efficient resource management and ensuring professional success. This paper explores the application of Bayesian analysis in higher education, specifically in the context of PBL, to demonstrate how this method allows for dynamic updating of beliefs about educational strategies based on accumulated data (Hersey & Blanchard, 1977).

A total of 404 educator subjects were analyzed, in 28 educational units through-out the country. Ten variables related to leadership, PBL and education were ap-plied. The integration of Bayesian analysis with PBL enhances the ability to quantitatively evaluate the impact of such innovative teaching methodologies on student outcomes, thereby contributing valuable insights into curriculum design and educational practices aimed at preparing students for professional success (Siemens & Long, 2011).

#### 1.1. Origins of situational leadership

The concept of situational leadership was pioneered in the 1970s by Paul Hersey and Kenneth Blanchard. Their foundational book, "Management of Organizational Behavior: Utilizing Human Resources" (1977), articulated the theory that effective leadership is adaptive to its context, particularly to the 'maturity' level of the followers being led. Hersey and Blanchard



described maturity not just in terms of age or experience, but as a composite of ability and willingness to take responsibility for directing one's own behavior in organizational settings (Koedinger & Corbett, 2006).

#### 1.1.1. Fundamental principles of situational leadership

Situational leadership is characterized by its flexibility. It proposes that there is no single "best" style of leadership. Instead, effective leaders must adjust their management style to reflect the task at hand and the readiness level of their followers. This approach delineates four primary leadership styles:

- Directive Leadership: Employed when followers display low maturity and competence but are enthusiastic and committed. Leaders focus on specific instructions and close supervision.
- Supportive Leadership: Best suited for followers with moderate maturity, who have more competence but less commitment. Leaders provide support and encouragement to motivate staff.
- Participatory Leadership: Effective with followers who are competent and committed, capable of taking responsibility but require participation in decision-making to remain engaged.
- Delegative Leadership: Appropriate for followers with high levels of maturity, offering significant autonomy in how goals are accomplished (Dignum, 2018).

#### 1.1.2. Applications of situational leadership. Sector-specific applications

In Business: Situational leadership proves crucial in managing diverse teams and projects, where leaders must adapt their styles to the specific needs of different groups and evolving project phases.

In Education: This leadership style allows educators to tailor their instructional methods according to the varying readiness levels and learning styles of their students, potentially enhancing engagement and educational outcomes.

In Nonprofits: Here, situational leadership is vital for managing volunteers who come with a wide range of capabilities and motivations. By adapting leadership styles, nonprofits can maximize the effectiveness and satisfaction of their volunteers (Woods *et al.*, 2021).

- Impact on organizational effectiveness: Research supports that situational leadership significantly enhances organizational effectiveness. By adapting leadership behaviors to meet the specific needs of their team members, leaders can improve employee satisfaction, increase productivity, and foster an environment conducive to collaboration. This adaptability is especially beneficial during periods of organizational change, as it allows for more nuanced management that can address varying degrees of acceptance and readiness for change among employees (Zhu *et al.*, 2022).



- Empirical evidence: Studies such as Graeff (1983) have demonstrated the efficacy of situational leadership in enhancing group performance by matching leadership style to the specific developmental stage of the group, thereby optimizing communication and task allocation based on follower readiness (Lee, 2021).

#### 1.2. Elements about AI, original foundations, and applications

Artificial Intelligence (AI) represents a significant technological advancement, influencing various sectors including education. The ability to harness AI effectively within educational leadership and pedagogy is crucial for optimizing teaching methodologies and enhancing student learning experiences (VanLehn, 2011).

#### 1.2.1. Foundations of AI

AI fundamentally involves creating systems that can perform tasks typically requiring human intelligence. These tasks include decision-making, problem-solving, understanding language, and recognizing patterns. The formal establishment of AI as an academic discipline occurred at the Dartmouth Conference in 1956, where the foundational goals and principles were laid out. The integration of AI in education necessitates that educational leaders not only keep abreast of the latest technological advancements but also foster an environment that leverages these tools for effective teaching and learning. This requires a robust understanding of what AI can achieve and the foresight to apply these capabilities within the educational framework (Anderson *et al.*, 1995).

#### 1.2.2 Applications of AI

In education, AI has the potential to revolutionize the way educational content is delivered and how students interact with it. Applications include:

- Personalized Learning: AI algorithms can analyze data from student interactions and adapt instructional material to fit individual learning paces and preferences.
- Intelligent Tutoring Systems (ITS): These systems provide personalized instruction and feedback to students without the need for constant human oversight, allowing for a more scalable and individualized learning experience.
- Educational Data Mining: AI techniques are used to discover patterns in large sets of educational data, which can inform policy and decision-making processes (Greller & Drachsler, 2012).

#### 1.2.3. AI in educational leadership

Effective integration of AI in educational settings requires leaders who can critically assess both the opportunities and the limitations of these technologies. Educational leaders should:

- Develop and Implement AI Strategies: Create comprehensive strategies for incorporating AI technologies that align with educational goals.
- Ensure Ethical Use of AI: Address ethical concerns related to AI use in education, including privacy, security, and fairness.



- Promote AI Literacy: Encourage educators and students to gain a basic understanding of AI, fostering a learning environment that is adept at integrating new technologies (Bessen, 2019).

#### 1.2.4. AI-Enhanced pedagogy

AI can significantly enhance the pedagogical process by providing more personalized and engaging learning experiences. Key applications include:

- Adaptive Learning Platforms: Use AI to adjust the content, pace, and complexity of material based on real-time assessments of student performance.
- Virtual Assistants: Implement AI-driven virtual assistants to help manage the administrative tasks for teachers, allowing them to focus more on teaching.
- Simulation and Virtual Reality: Employ AI in simulations and virtual reality to create immersive learning environments for students (Kapoor & Dwivedi, 2021).

#### 1.2.5. Challenges and ethical considerations

While AI offers substantial benefits, it also presents several challenges:

- Data Privacy: Ensuring the privacy and security of student data is paramount as more personal information is used by AI systems.
- Algorithmic Bias: Leaders need to be vigilant of potential biases in AI algorithms that could lead to unfair treatment of certain student groups.
- Access and Equity: It is essential to address the digital divide that may prevent some students from accessing AI-enhanced learning tools, which can exacerbate existing educational inequalities (Chui & Manyika, 2018).

#### 1.3. Relationship between AI and education

The interplay between Artificial Intelligence (AI) and education is reshaping educational methodologies, learner experiences, and administrative frameworks. This dynamic relationship enhances personalized learning and operational efficiency, but it also brings about significant ethical considerations that need to be meticulously managed (Wang, 2020).

#### 1.3.1. Pedagogical transformation through AI

AI is revolutionizing pedagogy by enabling more adaptive and responsive learning environments. Technologies such as machine learning algorithms and data analytics are being employed to create highly personalized education pathways and environments that respond to the individual needs of students. This includes dynamic adjustment of content difficulty, pacing based on student engagement and understanding, and interactive learning aids that simulate one-on-one tutoring (Nosenko, 2023).



#### 1.3.2. AI's role in personalized learning

AI's capability to harness vast amounts of educational data has transformed personalized learning. By analyzing patterns in student performance, AI systems can identify each student's strengths, weaknesses, learning speeds, and preferences. This data-driven approach enables the delivery of customized content and assessments, optimizing learning outcomes and enhancing student engagement (Pappas & Pigueiras, 2019).

#### 1.3.3. Institutional adoption of AI

Educational institutions are integrating AI to enhance operational efficiency and student services. AI applications range from automating administrative tasks such as admissions and scheduling to advanced systems for tracking student progress and predicting educational outcomes. This adoption not only saves valuable time and resources but also improves decision-making processes at various institutional levels (Thakur & Sharma, 2020).

#### 1.3.4. Ethical considerations in AI education

The deployment of AI in education necessitates a critical focus on ethical issues, such as data privacy, security, and algorithmic fairness. Ensuring the transparency of AI systems and safeguarding sensitive student information are paramount. Institutions must develop robust policies and frameworks to govern the ethical use of AI, promoting transparency and accountability (Dennen & Burner, 2008).

#### 1.3.5. AI and inclusive education

While AI offers tools that can potentially transform education, it is crucial that these technologies are accessible to all students, including those from diverse backgrounds and with different learning abilities. AI systems must be designed to support inclusive educational practices that prevent the exacerbation of existing disparities. This includes providing AI resources in multiple languages and formats suitable for students with disabilities (Lynch & Dembo, 2004).

The relationship between Artificial Intelligence (AI) and education is a dynamic and evolving interplay that holds the potential to transform various aspects of the educational experience. This transformation spans pedagogical approaches, personalized learning experiences, institutional efficiency, and ethical considerations.

AI is revolutionizing pedagogy by creating more adaptive and responsive learning environments. Technologies like machine learning algorithms and data analytics enable highly personalized education pathways, dynamically adjusting content difficulty and pacing based on student engagement and understanding. Interactive learning aids and one-on-one tutoring simulations further enhance the learning experience by catering to individual student needs (Nosenko, 2023).

AI's capacity to analyze vast amounts of educational data has significantly improved personalized learning. By identifying patterns in student performance, AI systems can pinpoint each student's strengths, weaknesses, learning speeds, and preferences. This datadriven approach facilitates the delivery of customized content and assessments, optimizing learning outcomes and boosting student engagement (Pappas & Pigueiras, 2019).



Educational institutions are increasingly adopting AI to enhance operational efficiency and student services. AI applications streamline administrative tasks such as admissions and scheduling, track student progress, and predict educational outcomes. This technological integration saves time and resources while improving decision-making processes across institutional levels (Thakur & Sharma, 2020).

The ethical deployment of AI in education is paramount, focusing on data privacy, security, and algorithmic fairness. Ensuring transparency of AI systems and safeguarding sensitive student information are critical. Institutions must develop robust policies and frameworks to govern the ethical use of AI, promoting transparency and accountability (Dennen & Burner, 2008).

AI also plays a crucial role in promoting inclusive education. It is essential that AI technologies are accessible to all students, regardless of their backgrounds or learning abilities. Designing AI systems to support inclusive educational practices helps prevent the exacerbation of existing disparities. This includes providing AI resources in multiple languages and formats suitable for students with disabilities (Lynch & Dembo, 2004).

#### **1.4.** AI in the process of university education

AI tools can enhance the university education process by offering intelligent tutoring systems, automating administrative tasks, and facilitating personalized learning plans. Universities adopting AI technologies can provide a more dynamic and effective educational experience.

The integration of Artificial Intelligence (AI) into university education heralds a transformative era, reshaping pedagogical methods, streamlining administrative operations, and refining the educational experience. This evolution is underscored by a growing reliance on AI to enhance both academic and operational efficiencies, fostering a more engaging and inclusive learning environment (Baker & Inner, 2014).

#### 1.4.1. Intelligent tutoring systems (ITS) in higher education

Intelligent Tutoring Systems (ITS) represent a significant advancement in educational technology, utilizing AI to provide customized educational experiences. These systems are designed to adapt to the learning pace and style of individual students, offering real-time feedback, personalized tutoring, and adaptive assessment. ITS tools analyze student responses and tailor the instructional content accordingly, ensuring that students receive support precisely at their points of need. This personalized learning approach has been shown to improve student performance and engagement dramatically (Turing, 2021).

#### 1.4.2. AI-Driven learning analytics

AI-driven learning analytics utilize machine learning algorithms to process extensive data sets on student interactions and outcomes, enabling educators to uncover insights into student behaviors and learning patterns. This approach facilitates a deeper understanding of educational dynamics, helping institutions to identify at-risk students, tailor educational interventions, and optimize curriculum designs to improve educational outcomes (Woolf, 2010).



Virtual classrooms and AI-powered teaching assistants are pivotal in broadening the reach and accessibility of education. These technologies enable institutions to offer flexible, scalable, and accessible learning options. AI assistants can manage routine inquiries, provide tutoring, and facilitate discussions, thereby allowing human educators to focus on more complex educational tasks. Furthermore, these tools can break down geographical and physical barriers, making high-quality education accessible to a wider audience (Luckin *et al.*, 2016).

#### 1.4.4. Automating administrative processes

AI technologies automate and optimize various administrative tasks in universities, including admissions, registration, and scheduling. These systems can analyze historical data to predict enrollment trends, optimize class schedules based on student preferences and faculty availability, and streamline resource allocation. By reducing the manual workload and minimizing human error, AI significantly enhances operational efficiency and allows administrative staff to engage more deeply in student support and strategic planning (Graeff, 1983).

#### 1.4.5. Ethical considerations in AI-integrated education

As AI becomes more embedded in educational contexts, ethical considerations must be at the forefront of its deployment. Concerns include ensuring data privacy, maintaining transparency in AI-driven decisions, and preventing bias in AI algorithms. Universities must develop comprehensive policies and guidelines to govern AI use, safeguard student information, and ensure that AI tools are used responsibly to support educational equity and integrity (Northouse, 2015).

The relationship between AI and university education is multifaceted, impacting both teaching and administrative processes. Intelligent Tutoring Systems (ITS) enhance the learning experience by providing personalized feedback and instruction tailored to individual student needs, significantly boosting engagement and performance. AI-driven learning analytics offer deep insights into student behaviors, enabling educators to identify at-risk students and customize interventions to improve outcomes.

Virtual classrooms and AI-powered teaching assistants expand access to education, breaking down geographical barriers and allowing for more flexible learning environments. These tools manage routine tasks, freeing up human educators to focus on more complex and impactful teaching activities.

Administrative processes in universities are also streamlined through AI, which automates tasks such as admissions and scheduling, thereby enhancing operational efficiency and reducing human error. This allows administrative staff to allocate more time and resources to strategic planning and student support.

However, the integration of AI in education also necessitates careful consideration of ethical issues, including data privacy, transparency, and algorithmic fairness. Universities must establish robust policies to govern the ethical use of AI, ensuring that these technologies are deployed responsibly and equitably.



As the job market evolves, the integration of Artificial Intelligence (AI) tools in education systems becomes crucial to prepare students effectively for future careers. These tools not only help in aligning educational outcomes with industry requirements but also in personalizing the learning experience to enhance employability (Yukl, 2012).

#### 1.5.1. AI-Powered skill development

AI-powered platforms in education can profoundly impact skill development by personalizing learning experiences based on labor market trends and individual learner profiles. Through the use of big data analytics and machine learning algorithms, these platforms identify skills in high demand across industries and tailor educational content to fill gaps in the job market. This approach ensures that curricula remain relevant and that students are equipped with the necessary tools to navigate a rapidly changing economic landscape (Selwyn, 2017).

#### 1.5.2. AI-Enhanced career counseling

AI-enhanced career counseling utilizes sophisticated algorithms to process large datasets, enabling personalized guidance for students. These systems analyze historical employment data, emerging job trends, and individual student achievements to provide tailored career advice. By aligning students' strengths and interests with market needs, AI-driven career counseling helps in making informed decisions about their professional futures (Veletsianos, & Doering, 2010).

#### 1.5.3. AI in internship and work placement matching

Integrating AI in the matching process for internships and work placements can significantly enhance the relevance and quality of professional training that students receive. By analyzing detailed profiles of both students and employers, AI algorithms can facilitate optimal matches, ensuring that students acquire hands-on experience that is closely aligned with their academic and career goals. This targeted matching process not only benefits students by providing relevant experience but also employers who gain access to candidates with the most suitable skill sets (Van den Berghe *et al.*, 2019).

#### 1.5.4. AI-Embedded professional development

In today's dynamic job market, continuous professional development is crucial. AI-driven learning platforms provide personalized recommendations for courses and certifications based on emerging industry trends and individual career trajectories. These platforms use predictive analytics to suggest training programs that are most likely to benefit the user, ensuring continual skill enhancement and adaptability in the workforce (Siemens & Baker, 2012).

#### 1.5.5. AI for adaptive learning paths

AI-driven adaptive learning systems dynamically adjust educational content and pacing based on continuous assessment of a student's performance. This personalized learning approach ensures that each student masters essential skills efficiently and effectively. By adapting to individual learning styles and speeds, these systems help prepare students for real-world challenges, aligning academic progress with personal and professional goals. (Lane *et al.*, 2015)



# 2. Methodology

#### 2.1. Application of the Bayesian model in education

The application of Bayesian analysis within the context of Project-Based Learning (PBL) in higher education entails a systematic collection and evaluation of student performance data to refine and enhance educational strategies. This process leverages Bayesian methodologies to assimilate and reinterpret data in light of pre-existing knowledge and empirical evidence. Specifically, a Bayesian framework might commence with preconceived notions about the efficacy of PBL, derived from existing literature. As contemporary data from recent PBL implementations are integrated, Bayesian analysis facilitates the modification of these initial beliefs, yielding a more precise assessment of PBL's effectiveness in bolstering professional competencies.

A concrete implementation of Bayesian analysis in this domain could manifest as follows: a university might deploy a novel curriculum predicated on PBL principles within selected courses aimed at cultivating professional skills such as teamwork, problem-solving, and selfmanagement. Throughout the academic term, performance metrics from students are meticulously collected through diverse evaluative measures. These data are then scrutinized using Bayesian techniques that consider both the foundational hypotheses (prior) and the new empirical data (likelihood). The outcomes (posterior) of this analysis offer an updated and nuanced perspective on the impact of PBL on professional competencies, serving as a valuable tool for informed curriculum development.

Furthermore, the Bayesian approach is adept at managing the inherent complexities associated with varying student backgrounds and disparate levels of prior knowledge, establishing a robust framework for educational evaluation. This methodology not only supports the assessment of current educational practices but also aids in the development of predictive models. These models are capable of forecasting future student performance trends across different educational interventions, thus facilitating strategic planning and resource allocation.

#### Table 1.

Application Bayesian Model			
Likelihood:			
LidEd ~ regress(xb_LidEd,{sigma2})			
Priors:			
{LidEd:RegSen Tit Instrab AnExp _cons} ~ norma	1 (0,10000) (1)		
{sigma2} ~ igamma (.01,.01)			
(1) Parameters are elements of the linear form xt	_LidEd.		
Bayesian linear regression	MCMC iterations = $120500$		
Random-walk Metropolis-Hastings sampling	Burn-in = 2.500		
	MCMC sample size = $10.000$		
	Number of $obs = 404$		
	Acceptance rate = $0,3203$		
	Efficiency: min = 0,01844		
	avg = 0,06309		
Log marginal-likelihood = -446.54118	max = 0,2071		
Equal-tailed			
Mean Std. dev. MCSE	Median [95% cred. interval]		
LidEd			



RegSen	0,1359099	0,0881891	0,00476	0,1385908	-0,0335373	0,312053
Tit	0,0212238	0,0303384	0,001496	0,0218975	-0,0380822	0,0779405
Instrab	-0,0011243	0,0388156	0,002858	-0,0018696	-0,0739477	0,074643
AnExp	0,0030473	0,0229377	0,001054	0,0038316	-0,0419301	0,0468522
_cons	1,535916	0,1453004	0,00836	1,539523	1,25656	1,818508
sigma2	0,4330216	0,0310247	0,000682	0,431523	0,3762855	0,4973949

Fuente: Self-made (2024).

Interpretation of Parameters

**RegSen** Coefficient: 0,1359 Standard Deviation: 0,0882

Interpretation: The coefficient for RegSen suggests that, on average, having more registered degrees is positively associated with higher levels of educational leadership. However, the 95% credible interval crosses zero, indicating that the effect of registered degrees on educational leadership is not statistically significant at the 95% confidence level. This means we cannot confidently assert that more registered degrees lead to higher educational leadership without further evidence.

**Tit Coefficient:** 0,0212 Standard Deviation: 0,0303

Interpretation: This small and positive coefficient suggests a slight positive effect of holding a third-level degree on educational leadership. However, like RegSen, the credible interval includes zero, suggesting this relationship is not statistically significant.

**Instrab** Coefficient: -0,0011 Standard Deviation: 0,0388

Interpretation: The coefficient is close to zero with a credible interval that widely spans zero, indicating no significant relationship between the type of institution where one works and their level of educational leadership.

**AnExp** Coefficient: 0,0030 95% Credible Interval: [-0,0419; 0,0469]

Interpretation: The coefficient is positive but very small, suggesting that years of experience might have a very slight positive effect on educational leadership. However, the credible interval includes zero, indicating that this effect is not statistically significant.

Constant (\_cons) Coefficient: 1,536 95% Credible Interval: [1,2566; 1,8185]

Interpretation: The intercept is significantly different from zero, indicating that the base level of educational leadership (when all independent variables are zero) is positive and significant.



In the second model, the relationship between variables is recreated:

Dependent: LidEd: Educational leadership. and Independent: CatLid: Leadership Chair, PrCol: Colmena Project, EjLid:Leadership exercise, CurrEst: Curricular strategies, DesInt: Institutional development.

#### Table 2.

Amplication	Bayesian Model						
Likelihood	<u> </u>						
	gress(xb_LidE	d,{sigma2})					
Priors:	0 ( =						
{LidEd: Ca	tLid PrCol EjL	id CurrEst D	esInt _cons}	~ normal (0,10	000) (1)		
{sigma2} ~	igamma(.01,.0	1)		,	, , ,		
(1) Parame	eters are eleme	nts of the lin	ear form xb	LidEd.			
Bayesian linear regression				MCMC iterations = $12,500$			
Random-walk Metropolis-Hastings sampling				Burn-in = 2,500			
			MCMC sample size = $10,000$				
				Number of obs $=$ 404			
				Acceptance rate $=$ .3054			
				Efficiency: min = .02676			
				avg = .05787			
Log marginal-likelihood = -416.13748				max = .1982			
Equal-taile	ed						
	Mean	Std. dev.	MCSE	Median	[95% cred. interval]		
LidEd							
C . IT ! 1							
CatLid	0,3865651	0,0459882	0,002535	0,385205	0,2963424	0,479366	
PrCol	0,3865651 0,0429939	0,0459882 0,0287654	0,002535 0,001502	0,385205 0,0428815	0,2963424 -0,0129351	0,479366 0,0991341	
				· · · · · · · · · · · · · · · · · · ·		· · · · · · · · · · · · · · · · · · ·	
PrCol	0,0429939	0,0287654	0,001502	0,0428815	-0,0129351	0,0991341	
PrCol EjLid	0,0429939 0,015128 -	0,0287654 0,0369762	0,001502 0,00226	0,0428815 0,0147384	-0,0129351 0,0556175	0,0991341 0,0886539	
PrCol EjLid CurrEst	0,0429939 0,015128 - -0,0574121	0,0287654 0,0369762 0,0380654	0,001502 0,00226 0,002186	0,0428815 0,0147384 -0,0582255	-0,0129351 0,0556175 -0,1319721	0,0991341 0,0886539 0,0201893	

Fuente: Self-made (2024).

In this model, the dependent variable is LidEd (Educational Leadership), and the independent variables are CatLid (Leadership Chair), PrCol (Beehive Project), EjLid (Leadership Exercise), CurrEst (Curricular Strategies), and DesInt (Institutional Development). The objective is to assess how these various leadership and institutional factors contribute to educational leadership outcomes. The model uses Bayesian linear regression with priors specified as normal for the regression coefficients and inverse gamma for the variance of residuals.

#### Interpretation of Parameters

**CatLid** Coefficient: 0,3866 Standard Deviation: 0,0460



Interpretation: The coefficient for CatLid is positive and significantly different from zero (as the 95% credible interval does not include zero). This suggests a strong and positive association between holding a leadership chair and higher levels of educational leadership. The role seems to have a substantial impact on leadership outcomes, indicating its effectiveness in promoting leadership qualities.

**PrCol** Coefficient: 0,0430 Standard Deviation: 0,0288

Interpretation: The effect of the Beehive Project is positive but not statistically significant since the 95% credible interval includes zero. This indicates that while there may be a positive trend, it is not robust enough to be deemed a reliable influencer of educational leadership within the data's constraints.

**EjLid** Coefficient: 0,0151 Standard Deviation: 0,0370

Interpretation: The coefficient for leadership exercises is small and the credible interval includes zero, suggesting no significant impact of this variable on educational leadership outcomes. The exercises might not be effectively designed or implemented to make a noticeable impact.

**CurrEst** Coefficient: -0,0574 Standard Deviation: 0,0381

Interpretation: The negative coefficient for curricular strategies, although not significant (since the interval includes zero), suggests a potential adverse effect on educational leadership. This could indicate that the strategies being implemented are not aligning well with leadership development goals or are perhaps not being effectively integrated into the curriculum.

**DesInt** Coefficient: 0,1031 Standard Deviation: 0,0378

Interpretation: This variable shows a positive and significant effect on educational leadership. The development of institutional frameworks and resources appears to be an effective means of enhancing leadership qualities among educational leaders.

**Constant** (\_cons) Coefficient: 0,9355 Standard Deviation: 0,1063

Interpretation: The intercept is significantly different from zero, indicating that when all independent variables are at zero, the expected level of educational leadership is still positive and substantial.

# 3. Results

#### 3.1. Comparative Analysis of Both Bayesian Models on Educational Leadership

The two models presented use Bayesian linear regression to analyze the influence of various factors on educational leadership (LidEd). Each model focuses on different sets of variables, which allows us to examine educational leadership from multiple perspectives within the context of Project-Based Learning (PBL).



Model 1 Analysis: Variables: Registered degrees (RegSen), Third-level degree (Tit), Institution type (Instrab), and Years of experience (AnExp).

Findings: In this model, none of the coefficients for the independent variables were statistically significant as their 95% credible intervals included zero. This suggests that while intuitively these factors might influence leadership, the evidence does not robustly support their impact.

Model 2 Analysis: Variables: Leadership Chair (CatLid), Beehive Project (PrCol), Leadership exercise (EjLid), Curricular strategies (CurrEst), Institutional development (DesInt).

Findings: This model showed that holding a leadership chair (CatLid) and institutional development (DesInt) significantly enhance educational leadership. Both have credible intervals that do not include zero, highlighting their positive impacts. However, curricular strategies (CurrEst) had a potentially negative impact, though not statistically significant.

Effectiveness of Leadership Positions: The significant positive impact of the leadership chair in Model 2 underscores the importance of formal leadership roles in enhancing educational leadership capabilities.

Institutional Influence: Institutional development has a clear and positive impact on leadership, suggesting that organizational policies and frameworks significantly influence leadership qualities.

Variable Significance: Across both models, most educational and experiential variables like degree types, years of experience, and specific projects did not significantly predict leadership outcomes, indicating that personal and institutional factors might be more crucial.

# 4. Discussion

In the discussion section we begin by talking about the Basic Elements on Leadership: Situational leadership, pioneered by Hersey and Blanchard, emphasizes adapting leadership styles to follower maturity and specific situations. This flexibility is crucial in dynamic environments. The four leadership styles–Directive, Supportive, Participative, and Delegative–offer a comprehensive framework for effective leadership.

Originating in the 1970s, situational leadership addressed limitations in fixed leadership models. Hersey and Blanchard's foundational work emphasized the dynamic relationship between leaders and followers. The model's endurance highlights its relevance in navigating contemporary leadership challenges.

Applications of Situational Leadership: Situational leadership finds application in diverse fields, demonstrating its versatility. In business, education, and nonprofits, it enables leaders to tailor their approaches. Its positive impact on organizational effectiveness is evident through improved satisfaction, productivity, and adaptability to change.

AI Tools Adapted to the Current Labor Market: The integration of AI in education aligns with evolving labor market demands. AI facilitates personalized skill development, enhances career counseling, optimizes internship matching, supports continuous professional development, and enables adaptive learning paths. These applications underscore AI's role in preparing students for career success.



Relationship Between AI and Education: AI's role in education is transformative, influencing pedagogical approaches, personalization, and accessibility. The partnership between AI and education is instrumental in creating adaptive, data-driven learning environments. AI's potential extends to addressing challenges such as individualized instruction, timely feedback, and equitable access to quality education.

# **5.** Conclusions

Situational leadership's adaptability aligns with the dynamic nature of contemporary challenges, emphasizing the importance of tailoring leadership to specific contexts and follower maturity.

The longevity of situational leadership attests to its enduring relevance. Its incorporation of follower maturity as a central element distinguishes it from static leadership models.

The integration of AI in education marks a transformative shift, enhancing personalized learning, career guidance, and skill development. AI's ability to analyze data and provide tailored solutions contributes to more effective and efficient educational processes. The synergy between dynamic leadership models, like situational leadership, and the transformative potential of AI in education creates a powerful framework for preparing students for success in a rapidly evolving world. Continuous adaptation, collaboration, and ethical considerations are essential for leveraging these approaches effectively.

The integration of AI in education requires thoughtful leadership to ensure that technological advancements contribute positively to educational outcomes. By understanding and addressing the foundations, applications, and challenges of AI, educational leaders can provide ethical guidance and innovative solutions that enhance teaching and learning.

#### 5.1. Recommendations

Incorporate situational leadership training in educational programs for leaders and managers to enhance their adaptability and effectiveness.

Educational institutions should continuously explore and integrate AI tools to align curricula with industry demands, ensuring graduates are well-prepared for the workforce. Encourage ongoing research to explore the intersection of AI and education, identifying new opportunities and potential challenges.

Foster collaboration between educators, industry professionals, and AI developers to create synergies that enhance the educational experience and bridge the gap between academia and the job market. Prioritize ethical considerations in the development and implementation of AI tools, ensuring that they enhance education without compromising privacy or perpetuating biases.

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#### **Contributions of the Authors:**

**Conceptualization:** Donoso Vargas, Diego; **Software:** Gallardo Cornejo, Ana María **Validation:** Gallardo Cornejo, Ana María; **Formal Analysis:** Gallardo Cornejo, Ana María; **Data curation:** Gallardo Cornejo, Ana María; **Writing-Preparation of the original draft:** Donoso Vargas, Diego; **Drafting-Revision and Editing:** Donoso Vargas, Diego **Visualization:** Gallardo Cornejo, Ana María; **Project Administration:** Donoso Vargas, Diego **All Authors have read and accepted the published version of the manuscript:** Donoso Vargas, Diego and Gallardo Cornejo, Ana María

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AUTHORS:

#### Diego José Donoso Vargas:

ECOTEC Technological University.

PhD in Political Science, PhD in Public Administration. Leader of the International Business and Public Administration Collective, ECOTEC. Visiting Professor - Postdoctoral Researcher Universidad Complutense de Madrid, Universidad de Granada, Universidad de Málaga and Universidad de DEUSTO.

ddonoso@ecotec.edu.ec

H index: 3

Orcid ID: https://orcid.org/0000-0002-9961-5405 Scopus ID: https://www.scopus.com/authid/detail.uri?authorId=57212194215 ResearchID: https://www.webofscience.com/wos/author/record/R-1332-2016 Google Scholar: https://scholar.google.com/citations?user=AICFj8IAAAAJ&hl=es

#### Ana María Gallardo:

ECOTEC Technological University.

Former ViceMinister of Exports and Investments Promotion/Executive Director/ International Business/ Former Trade Commissioner of Ecuador/Dean of Economics and Global Studies. Harvard University, Innovation and Entrepreneurship Program Innovation and Entrepreneurship Program IDE Business School. Universitat Pompeu Fabra, Master International Business, Latin America, Asia and Europe. agallardo@ecotec.edu.ec

Orcid ID: <u>https://orcid.org/0009-0008-5545-3927</u>