

Transformational Leadership, Followership, and Agentic AI Adoption in Agribusiness Project Efficiency in Bamenda, Cameroon

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Abstract

Purpose: This study examines how transformational leadership and followership dynamics shape the adoption of agentic artificial intelligence (AI) and its influence on the efficiency of agribusiness projects in Bamenda, Cameroon.

Research Methodology: An explanatory sequential mixed methods design combined survey data from 278 agribusiness project leaders and team members with semi structured interviews with 12 organizational leaders. Quantitative data were analyzed with hierarchical regression and bootstrapping in SPSS version 27 and the PROCESS macro, and qualitative data were analyzed thematically following the six phase procedure of Braun and Clarke.

Results: Agentic AI adoption significantly enhanced project efficiency ($\beta=0.248$, $p<0.001$). Transformational leadership positively moderated this relationship ($\beta=0.147$, $p=0.007$), with the strongest effect at high leadership levels ($\beta=0.342$). Followership enacted team learning behavior partially mediated the relationship (indirect effect = 0.086, 95% CI [0.032, 0.148]), and moderated mediation analysis confirmed that the indirect effect was conditional on transformational leadership.

Conclusions: Technological adoption alone is insufficient. The relational synergy between transformational leaders and engaged followers is essential for optimizing agribusiness outcomes in resource constrained environments.

Limitations: The study is confined to Bamenda in the Northwest Region of Cameroon, which limits generalizability, and its cross sectional data preclude definitive causal inferences.

Contributions: The study advances leadership and followership theory by showing that follower enacted learning is the mechanism through which leader facilitated technology adoption translates into performance, and it offers guidance for leader and follower development and context sensitive AI implementation.

Keywords: *Agentic Artificial Intelligence, Cameroon, Followership, Project Efficiency, Transformational Leadership*

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1. Introduction

Leadership and followership are relational processes through which individuals and collectives influence one another toward shared purposes. In an era of accelerating technological change, the

question of how leaders and followers jointly navigate the adoption of autonomous technologies has become central to leadership scholarship ([Uhl-Bien et al., 2022](#), [Larson & DeChurch, 2020](#)). Agentic artificial intelligence, characterized by autonomous goal directed behavior and the capacity to execute complex tasks without continuous human direction, represents a distinctive challenge to traditional leadership and followership relations because it introduces a nonhuman actor into the influence process ([Olutimehin et al., 2025](#)). Unlike conventional AI systems that react to inputs, agentic AI proactively plans, executes, and adapts actions in pursuit of specified objectives, extending the long running shift from AI as a tool toward AI as a partner in decision making ([Jarrahi, 2018](#), [Huang & Rust, 2021](#)). This raises profound questions for leadership studies about how transformational leaders articulate a vision for technologies that operate autonomously and how followers exercise agency in relation to intelligent systems.

In Cameroon, where agriculture contributes substantially to national output and supports the livelihoods of millions, the adoption of digital technologies, including AI, has gained momentum in areas such as crop monitoring, mapping, and decision support ([Aroba & Rudolph, 2024](#), [Ayim et al., 2022](#)). However, the presence of technological tools does not automatically translate into meaningful outcomes. Outcomes depend on the quality of the leadership and followership relations that shape how technology is interpreted, embraced, and enacted ([Cortellazzo et al., 2019](#), [Trenerry et al., 2021](#)).

Bamenda, the regional headquarters of the Northwest Region of Cameroon, presents a particularly compelling context for examining these dynamics. The municipality has experienced significant sociopolitical instability since 2016, which has disrupted agricultural supply chains, displaced farming populations, and created operational uncertainty for agribusiness enterprises ([Ako, 2023](#)). In such volatile contexts, the relational foundations of leadership and followership become paramount, because followers look to leaders for direction and leaders depend on followers for collective sensemaking and adaptive action.

Despite growing interest in AI adoption in African agriculture, the leadership and followership dimensions of technology adoption remain underexplored ([Chatterjee et al., 2023](#)). Transformational leadership, characterized by idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration, may serve as a critical relational condition that determines whether agentic AI adoption translates into tangible performance improvements ([Bansal, 2025](#), [Siangchokyoo et al., 2020](#)). Furthermore, team learning behavior, conceptualized as a followership enacted process through which team members collectively make sense of and adapt to new technologies, may function as the mechanism through which leader facilitated technology adoption influences project efficiency ([Edmondson, 1999](#), [Edmondson & Bransby, 2023](#)).

The agribusiness sector in Bamenda faces persistent challenges in project efficiency, including disrupted supply chains, limited market access, and operational uncertainty stemming from the ongoing sociopolitical crisis ([Ako, 2023](#)). Agentic AI technologies offer potential solutions for enhancing operational efficiency, but their adoption in Cameroonian agribusiness remains at an early stage, and the leadership and followership conditions under which these technologies yield performance benefits are not well understood ([Ako, 2026](#)). Existing research has focused primarily on technological and managerial factors and has overlooked the relational processes of leadership and followership that shape how technology is enacted in practice ([Olutimehin et al., 2025](#), [Schwaeke et al., 2025](#)). The specific problem this study addresses is the lack of empirical evidence on how transformational leadership and follower enacted team learning behavior shape the relationship between agentic AI adoption and agribusiness project efficiency in Cameroon.

This study pursues two objectives. The first is to examine the influence of agentic AI adoption on agribusiness project efficiency in Bamenda, Northwest Region of Cameroon. The second is to assess the moderating role of transformational leadership and the mediating role of follower enacted team learning behavior in this relationship.

2. Literature Review and Hypothesis/es Development

2.1 *Agentic AI Adoption*

Agentic artificial intelligence represents an advanced class of AI systems that go beyond the reactive capabilities of traditional and generative AI ([Olutimehin et al., 2025](#)). Traditional AI operates on rule based logic and generative AI produces content in response to prompts, whereas agentic AI possesses autonomous goal directed behavior, the capacity to plan and execute multistep tasks, and the ability to adapt to changing circumstances without continuous human intervention. From a leadership and followership perspective, agentic AI introduces a third actor into the influence process and requires leaders and followers to negotiate jointly the boundaries of human and machine agency ([Larson & DeChurch, 2020](#)). This makes agentic AI adoption a relational challenge rather than merely a technical one, because leaders and followers must construct new patterns of interaction that incorporate autonomous systems ([Arslan et al., 2022](#)).

In agribusiness, agentic AI applications include autonomous crop monitoring systems, predictive maintenance of agricultural equipment, dynamic supply chain optimization, and real time decision making that responds to market conditions ([Olutimehin et al., 2025](#), [Wolfert et al., 2017](#)). The potential benefits are substantial, including improved operational efficiency through autonomous task execution, better decisions through continuous environmental monitoring, and expanded human capacity for strategic activities ([Jarrahi, 2018](#)). These benefits depend, however, on whether organizations build the complementary capabilities needed to turn AI resources into value ([Mikalef & Gupta, 2021](#), [Chowdhury et al., 2023](#)). The social and ethical implications of AI in agriculture, including its effects on workers and rural communities, also require careful attention ([Ryan, 2023](#)).

2.2 *Agribusiness Project Efficiency*

Project efficiency refers to the extent to which projects achieve their objectives within the constraints of time, budget, and quality standards ([Ako & Baiye, 2025](#)). In agribusiness, efficiency covers not only conventional project metrics but also factors specific to agricultural production, such as the timeliness of planting and harvesting, the minimization of postharvest losses, the optimization of input use, and responsiveness to market conditions. Because many agribusiness activities are seasonal and their products perishable, efficiency is particularly critical, and delays in one phase can spread throughout the value chain. Agribusiness project efficiency is therefore a collective accomplishment that depends on how leaders and followers coordinate their efforts, particularly when integrating new technologies into established workflows ([Trenerry et al., 2021](#)).

2.3 *Transformational Leadership*

Transformational leadership, as conceptualized by [Bass and Riggio \(2006\)](#), has four dimensions. Idealized influence refers to charismatic role modeling, inspirational motivation to the articulation of compelling visions, intellectual stimulation to the encouragement of innovation and critical thinking, and individualized consideration to the provision of personalized support and coaching. Leaders who exhibit these behaviors inspire followers to transcend self interest for collective goals, stimulate creative problem solving, and support follower development ([Bansal, 2025](#)). Meta analytic evidence confirms that transformational leadership remains strongly associated with follower attitudes and performance, even when compared with newer leadership styles ([Hoch et al., 2018](#)).

In technology adoption contexts, transformational leaders are positioned to articulate a vision for how AI can serve collective purposes, stimulate innovative applications, and provide the support followers need to adapt to new technologies. Transformational leadership has been found to support employees during organizational change ([Faupel & Süß, 2019](#)) and to strengthen innovation capability through knowledge sharing ([Le & Lei, 2019](#)). Reviews of leadership in digitalized organizations similarly emphasize that leaders who combine vision with support and openness are better able to guide digital transformation ([Cortellazzo et al., 2019](#), [Henderikx & Stoffers, 2022](#), [Schiuma et al., 2022](#)). From a

leadership studies perspective, transformational leadership is particularly relevant because it emphasizes the relational and developmental aspects of influence rather than control.

2.4 Followership and Team Learning Behavior

Followership refers to the active and purposeful role that individuals play in relation to leaders and leadership processes ([Uhl-Bien et al., 2014](#)). Rather than passive compliance, followership involves proactive engagement, critical thinking, and the joint construction of leadership outcomes. In this study, team learning behavior is conceptualized as a followership enacted process through which team members collectively seek feedback, share information, ask questions, discuss errors, and experiment with new approaches ([Edmondson, 1999](#)). This framing positions followers as active agents in technology adoption rather than passive recipients of leader directives, and it is consistent with the view that follower transformation is the core mechanism of transformational leadership ([Siangchokyo et al., 2020](#)).

Followership enacted learning behavior is particularly relevant to agentic AI adoption because autonomous systems introduce uncertainty that requires continuous collective sensemaking, a process that cannot be led unilaterally but must be created by leaders and followers together. Psychological safety, the shared belief that a team is safe for interpersonal risk taking, is a key condition for such learning, and reviews show that it is consistently associated with learning, engagement, and performance ([Newman et al., 2017](#), [Frazier et al., 2017](#), [Edmondson & Bransby, 2023](#)). Employees who perceive AI as a threat to their careers may withdraw from learning ([Brougham & Haar, 2018](#), [Kong et al., 2021](#)), which makes supportive relational conditions essential.

2.5 Theoretical Framework

Transformational Leadership Theory, which originated with Burns and was extended by Bass, posits that effective leaders inspire followers to transcend self interest for the collective good through idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration ([Bass & Riggio, 2006](#)). The theory is particularly relevant to technology adoption because transformational leaders can articulate compelling visions for innovation, stimulate creative problem solving, and provide individualized support during change ([Bansal, 2025](#), [Faupel & Süß, 2019](#)). In the context of agentic AI adoption, it provides a lens for understanding how leaders shape the relational conditions under which technology enhances collective performance.

Followership Theory reconceptualizes followership as a relational role that is constructed together with leadership rather than subordinate to it ([Uhl-Bien et al., 2014](#)). The theory emphasizes that effective followership involves proactive engagement, critical judgment, and contributions to collective outcomes. In technology adoption, it provides a framework for understanding how team members actively shape the integration of new technologies through their learning behaviors rather than merely responding to leader directives ([Uhl-Bien et al., 2022](#)).

Team Learning Theory conceptualizes team learning as a process of reflection and action through which teams acquire and apply knowledge ([Edmondson, 1999](#)). Edmondson showed that psychological safety enables team learning behaviors that enhance performance, and later research has confirmed and extended this insight across many settings ([Edmondson & Bransby, 2023](#)). In technology adoption, team learning behavior serves as a mechanism through which AI capabilities are translated into performance improvements, as leaders and followers collectively make sense of new technologies and adapt their work processes. Technology acceptance research further shows that facilitating conditions and social influence shape whether people use new technologies effectively ([Venkatesh et al., 2016](#)), which reinforces the role of leaders and teams in AI adoption.

2.6 Empirical Review

[Ako \(2026\)](#) investigated AI augmented human resource practices and agripreneurial success in the Southwest Region of Cameroon and found that technology integration can enhance agripreneurial outcomes, although the effects are mediated by organizational capabilities. [Olutimehin et al. \(2025\)](#)

documented the economic value of agentic AI and its positive impact on business productivity in emerging economies. Research on AI capability shows that AI creates value for firms when it is combined with complementary human and organizational resources ([Mikalef & Gupta, 2021](#)), and studies of SMEs show that AI adoption improves business practices when organizations possess the necessary readiness ([Baabdullah et al., 2021](#), [Chatterjee et al., 2021](#)). However, these studies did not examine the leadership and followership conditions under which AI adoption yields performance benefits.

Regarding transformational leadership as a moderator, [Chatterjee et al. \(2023\)](#) found that digital leadership capability moderated the relationship between digital workplace adoption and organizational performance. [Bansal \(2025\)](#) argued that leadership engagement is a critical enabler of cultural transformation during AI adoption, as leaders who promote openness and trust create environments in which followers embrace new technologies. Dynamic capabilities for digital transformation also depend on leaders who can sense and seize technological opportunities and reconfigure resources ([Warner & Wäger, 2019](#)). These findings suggest that transformational leadership may serve as a boundary condition that determines whether AI adoption translates into performance improvements.

Regarding followership enacted learning as a mediator, the foundational work of [Edmondson \(1999\)](#) established team learning behavior as a driver of team performance. In technology adoption, team learning may serve as a mechanism through which AI capabilities are translated into performance improvements, and framing it as a followership enacted process highlights the active role team members play in making technology work in practice. [Ako et al. \(2025\)](#) observed that organizational capabilities mediate the relationship between governance practices and performance, which suggests that follower enacted learning processes may function in a similar way. Research on AI and workforce interaction likewise shows that deliberate human resource strategies are needed to sustain engagement and cooperation between employees and AI systems ([Arslan et al., 2022](#), [Budhwar et al., 2022](#)).

2.7 Research Gap and Hypotheses

Despite growing interest in AI adoption in African agriculture, significant gaps remain. First, most studies have examined AI adoption from technical or managerial perspectives and have overlooked the relational processes of leadership and followership that shape how technology is enacted in practice ([Olutimehin et al., 2025](#)). Second, agentic AI, as distinct from traditional or generative AI, has received limited empirical attention, particularly in African agribusiness ([Mhlanga, 2021](#), [Aroba & Rudolph, 2024](#)). Third, the mechanisms through which AI adoption influences project efficiency, including the potential mediating role of follower enacted team learning behavior, remain underexplored ([Ako, 2026](#)). Fourth, the moderating role of transformational leadership in the relationship between AI and performance has not been tested empirically in the Cameroonian agribusiness sector ([Chatterjee et al., 2023](#)).

This study addresses these gaps by testing a moderated mediation model in which transformational leadership moderates both the direct and indirect effects of agentic AI adoption on project efficiency, with followership enacted team learning behavior as the mediating mechanism. Hypothesis 1 (H_1) states that agentic AI adoption has a significant positive influence on agribusiness project efficiency in Bamenda. Hypothesis 2 (H_2) states that transformational leadership significantly moderates the relationship between agentic AI adoption and agribusiness project efficiency, such that the positive relationship is stronger at higher levels of transformational leadership. Hypothesis 3 (H_3) states that follower enacted team learning behavior mediates the relationship between agentic AI adoption and agribusiness project efficiency. Hypothesis 4 (H_4) states that transformational leadership moderates the indirect effect of agentic AI adoption on project efficiency through follower enacted team learning behavior.

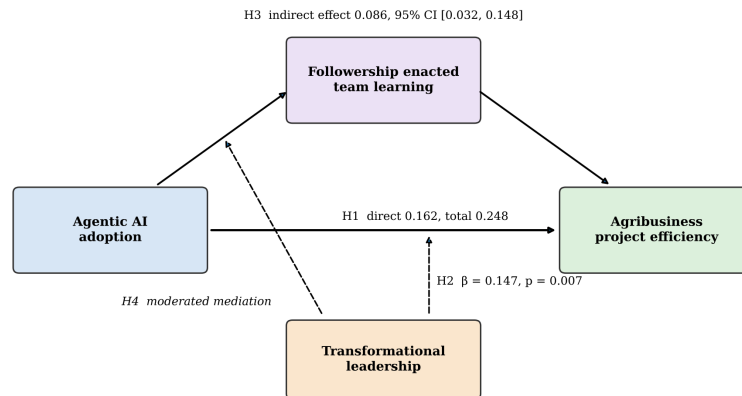


Figure 1. Moderated mediation model of agentic AI adoption, followership enacted team learning, transformational leadership, and agribusiness project efficiency

Figure 1 presents the moderated mediation model tested in this study together with the main estimates. The horizontal path from agentic AI adoption to project efficiency represents the direct effect tested in H_1 , while the upper path through followership enacted team learning represents the indirect effect tested in H_3 . The dashed arrows from transformational leadership show its moderating role on the direct path (H_2) and on the indirect path (H_4). The figure therefore summarizes the central argument of the study, namely that the value of agentic AI depends on both leaders and followers.

3. Research Methodology

3.1 Research Design

This study employed an explanatory sequential mixed methods design, in which quantitative data collection and analysis were followed by qualitative data collection and analysis that explain the quantitative results (Creswell & Plano Clark, 2018). This design was selected because it allows statistical testing of the hypothesized relationships while providing contextual depth for understanding the relational mechanisms and conditions of leadership and followership in technology adoption.

3.2 Study Area

The study was conducted in Bamenda, the regional headquarters of the Northwest Region of Cameroon. Bamenda serves as a hub for agribusiness activity, with enterprises engaged in crop production, livestock, and agro processing (Ako, 2023). The region has experienced significant sociopolitical instability, which creates a context in which both the potential benefits and the challenges of technology adoption are heightened.

3.3 Population and Sampling

The target population comprised project leaders, team leaders, and team members in agribusiness projects in Bamenda. Purposive sampling was used for the quantitative phase, supplemented by snowball sampling. Power analysis indicated a minimum sample of 250 for detecting medium effect sizes with adequate power. A total of 350 questionnaires were distributed, and 278 valid responses were retained, yielding a response rate of 79.4 percent. For the qualitative phase, 12 participants were purposively selected from the quantitative sample based on their leadership roles and willingness to take part in follow up interviews. Maximum variation sampling ensured diversity across agribusiness sectors and organizational sizes (Braun & Clarke, 2021).

3.4 Measures

Agentic AI adoption was measured with a five item scale adapted from technology adoption instruments, assessing the adoption of autonomous AI tools for project functions (Olutimehin et al.,

[2025, Venkatesh et al., 2016](#)). Transformational leadership was measured with the Multifactor Leadership Questionnaire short form, assessing idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration ([Bass & Riggio, 2006](#)). Followership enacted team learning behavior was measured with an adapted version of the Team Learning Behavior Scale of [Edmondson \(1999\)](#), with items framed to capture follower agency in seeking feedback, sharing information, and experimenting with new approaches. Project efficiency was measured with a six item scale assessing the achievement of objectives within time, budget, and quality constraints ([Ako & Baiye, 2025](#)). Organizational size, project duration, and respondent experience were included as control variables.

3.5 Data Collection

Quantitative data were collected between March and June 2026 using self administered questionnaires distributed in person and by email. Qualitative data were collected through semi structured interviews conducted between July and August 2026. Each interview lasted 45 to 75 minutes and was audio recorded with consent and transcribed verbatim.

3.6 Data Analysis

Quantitative data were analyzed using SPSS version 27 and the PROCESS macro ([Hayes, 2022](#)). Hierarchical regression tested direct and moderating effects, bootstrapping with 5.000 resamples tested mediation, and moderated mediation analysis tested conditional indirect effects. Qualitative data were analyzed through thematic analysis following the six phase procedure of [Braun and Clarke \(2021\)](#). Transcripts were coded, themes were developed, and the findings were integrated with the quantitative results through a joint display.

3.7 Ethical Considerations

Ethical approval was obtained before data collection. Participants were informed about the purpose of the study and provided informed consent, participation was voluntary, and data were anonymized during analysis and reported only in aggregate form.

4. Results and Discussions

4.1 Descriptive Statistics

Table 1. Demographic characteristics of respondents

Characteristic	Category	Frequency	Percentage
Gender	Male	170	61.2
	Female	108	38.8
Age	21 to 30 years	94	33.8
	31 to 40 years	124	44.6
	41 to 50 years	48	17.3
	51 years and above	12	4.3
Education	High school	38	13.7
	Bachelor degree	146	52.5
	Master degree	79	28.4
	Doctorate	15	5.4
Role	Project leader	107	38.5
	Team leader	88	31.7
	Team member	83	29.9

Table 1 presents the demographic characteristics of the 278 respondents, based on the field survey conducted in 2026. The majority of respondents were male (61.2 percent), and most held a bachelor's

degree (52.5 percent) or a master's degree (28.4 percent). The largest age group was 31 to 40 years (44.6 percent). Project leaders made up 38.5 percent of the sample, team leaders 31.7 percent, and team members 29.9 percent, which means that both leader and follower perspectives are well represented in the data.

4.2 Reliability Analysis

Table 2. Reliability analysis of the study scales

Scale	Items	Cronbach alpha
Agentic AI adoption	5	0.847
Transformational leadership	20	0.891
Followership enacted team learning	7	0.823
Project efficiency	6	0.834

Table 2 reports the number of items and the Cronbach alpha coefficients of the four scales, based on the 2026 field survey. All coefficients exceed the commonly accepted threshold of 0.70, ranging from 0.823 for followership enacted team learning to 0.891 for transformational leadership. These results show that the scales have good internal consistency and provide a reliable basis for the correlation, regression, and moderated mediation analyses.

4.3 Correlation Analysis

Table 3. Correlation matrix of the study variables

Variable	1	2	3	4
1. Agentic AI adoption	1.00			
2. Transformational leadership	0.267***	1.00		
3. Followership enacted team learning	0.298***	0.334***	1.00	
4. Project efficiency	0.312***	0.389***	0.356***	1.00

Table 3 presents the correlations among the four study variables, where three asterisks denote $p < 0.001$, based on the 2026 field survey. Agentic AI adoption correlated positively with project efficiency ($r = 0.312$) and transformational leadership ($r = 0.267$). Transformational leadership showed the strongest correlation with project efficiency ($r = 0.389$), and followership enacted team learning correlated with both agentic AI adoption ($r = 0.298$) and project efficiency ($r = 0.356$). All correlations are significant and moderate in size, which supports the proposed relationships while indicating that the constructs are distinct.

4.4 Hypothesis Testing

The influence of agentic AI adoption on project efficiency (H_1) was tested through hierarchical regression. In Step 2, agentic AI adoption significantly predicted project efficiency ($\beta = 0.248$, $p < 0.001$), supporting H_1 .

Table 4. Hierarchical regression results

Step	Predictor	β	t	p	ΔR^2
1	Control variables				0.032
2	Agentic AI adoption	0.248	4.192	< 0.001	
	Transformational leadership	0.317	5.651	< 0.001	0.214
3	Agentic AI $\times$ transformational leadership	0.147	2.667	0.007	0.018

Table 4 summarizes the hierarchical regression results from the 2026 field survey. The control variables in Step 1 explained 3.2 percent of the variance in project efficiency. Entering agentic AI adoption and transformational leadership in Step 2 added 21.4 percent of explained variance, with

both predictors significant ($\beta=0.248$ and $\beta=0.317$, $p<0.001$). The interaction term in Step 3 added a further 1.8 percent and was significant ($\beta=0.147$, $p=0.007$), which indicates that transformational leadership strengthens the effect of agentic AI adoption on project efficiency.

The moderating role of transformational leadership (H_2) was examined through simple slopes analysis. The effect of agentic AI adoption was strongest at high levels of transformational leadership ($\beta=0.342$), moderate at mean levels ($\beta=0.248$), and weakest at low levels ($\beta=0.154$). H_2 is therefore supported.

Table 5. Simple slopes analysis for transformational leadership

Level of transformational leadership	Conditional effect	SE	<i>t</i>	<i>p</i>
Low (one SD below mean)	0.154	0.061	2.525	0.012
Mean	0.248	0.052	4.769	< 0.001
High (one SD above mean)	0.342	0.068	5.029	< 0.001

Table 5 shows the conditional effects of agentic AI adoption on project efficiency at low, mean, and high levels of transformational leadership, based on the 2026 field survey. The effect is significant at all three levels, but it more than doubles from 0.154 at one standard deviation below the mean to 0.342 at one standard deviation above the mean. This pattern indicates that agentic AI delivers its greatest efficiency gains when leaders articulate a clear vision, stimulate innovation, and support their followers.

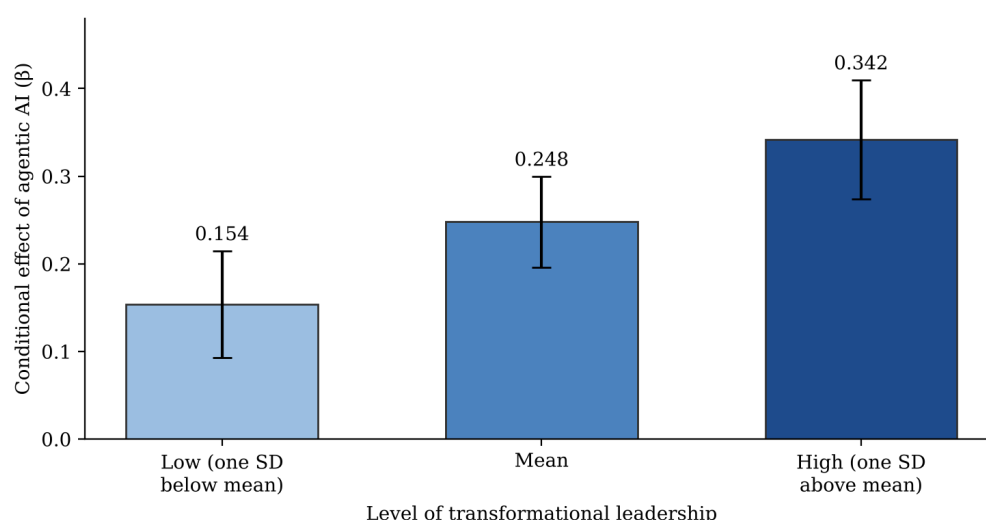


Figure 2. Conditional effect of agentic AI adoption on project efficiency at different levels of transformational leadership

Figure 2 visualizes the simple slopes reported in Table 5, with error bars showing one standard error. The bars rise steadily from low to high transformational leadership, making clear that the same level of agentic AI adoption produces much larger efficiency gains under strong transformational leadership. The figure therefore illustrates the moderating role of leadership stated in H_2 .

The mediating role of followership enacted team learning (H_3) was tested with bootstrapping. The indirect effect through followership enacted team learning was significant (indirect effect = 0.086, 95% CI [0.032, 0.148]), and the direct effect remained significant (direct effect = 0.162, $p<0.001$), indicating partial mediation. H_3 is therefore supported.

Table 6. Mediation analysis results

Effect	Estimate	SE	95% CI
Total effect	0.248	0.052	[0.146, 0.350]
Direct effect	0.162	0.054	[0.056, 0.268]
Indirect effect	0.086	0.029	[0.032, 0.148]

Table 6 presents the total, direct, and indirect effects of agentic AI adoption on project efficiency, based on 5,000 bootstrap samples from the 2026 field survey. None of the confidence intervals include zero, so all three effects are significant. The indirect effect through followership enacted team learning (0.086) accounts for about 35 percent of the total effect (0.248), while the direct effect (0.162) remains significant, which confirms partial mediation and shows that followers play a substantial role in translating AI adoption into efficiency.

Finally, the moderated mediation analysis (H_4) indicated that the indirect effect was conditional on transformational leadership. The conditional indirect effect was strongest at high levels of transformational leadership and weakest at low levels, which confirms that the mediated relationship is moderated by leadership behavior and supports H_4 .

4.5 Qualitative Findings

The thematic analysis produced four themes. The first theme concerns the perceived benefits of agentic AI adoption. Participants described tangible benefits, including better demand forecasting and faster decision making, and a project leader remarked that "The AI tools help us predict demand patterns and adjust production schedules accordingly."

The second theme presents transformational leadership as a catalyst. Participants emphasized leadership commitment as critical, and a team leader observed that "When the leader understands the technology and communicates its value clearly, the team is more willing to adopt it."

The third theme concerns follower agency in technology integration. Participants described how team members actively shaped the way AI tools were used in practice. A team member noted that "We had to figure out together how to make the system work for our specific crops. The leader gave us space to experiment."

The fourth theme presents team learning as the mechanism. A project coordinator explained that "What used to take days of manual analysis now takes hours. This frees our team to focus on implementation." This account illustrates how collective learning about AI tools releases time and attention for project execution.

4.6 Integration of Findings

Table 7. Joint display of quantitative and qualitative findings

Quantitative finding	Qualitative theme	Integration insight
AI adoption enhances efficiency	Perceived benefits	Tangible gains confirmed
Leadership moderates the relationship	Leadership as catalyst	Leaders create enabling conditions
Followership learning mediates the relationship	Follower agency in integration	Followers actively shape technology use

Table 7 integrates the quantitative and qualitative findings of the 2026 field study in a joint display. Each statistical result is matched with a qualitative theme that explains it. The positive effect of AI adoption is confirmed by participants' accounts of tangible gains, the moderating role of leadership is explained by leaders who create enabling conditions, and the mediating role of followership learning is illustrated by followers who actively shape how technology is used. The convergence of the two strands strengthens confidence in the proposed model.

4.7 Discussion

The finding that agentic AI adoption significantly enhances project efficiency ($\beta=0.248$, $p<0.001$) aligns with the documentation of the economic value of agentic AI by [Olutimehin et al. \(2025\)](#) and with evidence that AI capability improves firm performance ([Mikalef & Gupta, 2021](#)). The qualitative data provide explanatory depth, as participants described how AI tools improve forecasting accuracy and reduce administrative burden. This convergence suggests that agentic AI adoption yields tangible efficiency benefits in agribusiness, consistent with the findings of [Ako \(2026\)](#) on AI augmented human resource practices in Cameroon.

The significant moderating effect ($\beta=0.147$, $p=0.007$) provides empirical support for the relational perspective on technology adoption. The finding that the relationship between AI and efficiency is stronger at high transformational leadership ($\beta=0.342$) than at low transformational leadership ($\beta=0.154$) suggests that leaders who articulate compelling visions, stimulate innovation, and provide individualized support enable followers to realize greater value from AI adoption. This aligns with the finding of [Chatterjee et al. \(2023\)](#) that digital leadership capability acts as a moderator and supports the argument of [Bansal \(2025\)](#) that leadership engagement is critical during AI adoption. It is also consistent with evidence that transformational leadership helps employees cope with organizational change ([Faupel & Süß, 2019](#)) and with reviews that identify leadership as a decisive factor in digital transformation ([Cortellazzo et al., 2019](#), [Trenerry et al., 2021](#)). From a leadership studies perspective, transformational leadership operates as a relational condition that shapes how followers engage with new technologies.

The significant indirect effect (0.086, 95% CI [0.032, 0.148]) indicates that followership enacted team learning behavior partially mediates the relationship between AI and efficiency. This finding extends the team learning theory of [Edmondson \(1999\)](#) to technology adoption and advances followership theory by showing that followers are active agents in translating AI capabilities into performance improvements ([Uhl-Bien et al., 2014](#), [Siangchokyoo et al., 2020](#)). The qualitative finding that team members actively shaped how AI tools were used supports the conceptualization of followership as joint construction rather than passive compliance. The importance of learning also resonates with research showing that psychological safety enables teams to experiment and learn from errors ([Newman et al., 2017](#), [Edmondson & Bransby, 2023](#)).

The moderated mediation result indicates that transformational leadership also strengthens the learning pathway. Leaders who encourage questioning and experimentation create the psychological safety that followers need to explore autonomous systems, which in turn amplifies the efficiency gains from AI ([Frazier et al., 2017](#)). In a conflict affected setting such as Bamenda, this relational foundation may be especially important, because uncertainty and disruption can otherwise lead employees to see AI as a threat rather than an opportunity ([Brougham & Haar, 2018](#), [Kong et al., 2021](#)).

5. Conclusions

This study examined the influence of agentic AI adoption on agribusiness project efficiency in Bamenda, Cameroon, together with the moderating role of transformational leadership and the mediating role of followership enacted team learning behavior. The findings show that agentic AI adoption significantly enhances project efficiency, that this effect is amplified when leaders exhibit transformational behaviors, and that follower enacted team learning partially mediates the relationship, with the indirect effect also depending on leadership. Technology adoption alone is therefore insufficient, and its value is realized through the relationship between transformational leaders and engaged followers.

The study advances leadership and followership theory by identifying transformational leadership as a relational condition that enhances the value of agentic AI and followership enacted learning as the mechanism through which this value is realized, and it extends team learning theory to technology

adoption. In practice, leadership development programs should cultivate transformational competencies alongside technological skills, organizations should create conditions in which team members can shape how technologies are used, and development agencies and policymakers should include leader and follower development in initiatives that promote AI adoption.

The study is confined to Bamenda in the Northwest Region of Cameroon, which limits generalizability, and its cross sectional data preclude definitive causal inferences. Future research should test these findings in other African contexts, explore additional mediating mechanisms, and examine how the different dimensions of transformational leadership influence technology adoption outcomes.

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Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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