

AI Maturity as a Double-Edged Capability: Planning Fallacy and Firm Performance in Technology Startups

Mohammadreza Parsanejad

parsanejad@iust.ac.ir

Iran University of Science and Technology

Mohammadhasan Amiri

Iran University of Science and Technology

Yaser Sobhanifard

Iran University of Science and Technology

Javad Mashayekh

Iran University of Science and Technology

Research Article

Keywords: AI maturity, planning fallacy, firm performance, technology startups, entrepreneurial cognition, socio-technical systems theory, attention-based view

Posted Date: July 24th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10385386/v1>

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Additional Declarations: No competing interests reported.

Abstract

Artificial intelligence (AI) maturity is increasingly viewed as a source of advantage for technology startups, yet its value may depend on the planning assumptions guiding its use. Drawing on socio-technical systems theory, the attention-based view of the firm, and entrepreneurial cognition research, this study examines the relationship between planning fallacy and firm performance and tests the moderating role of AI maturity. Planning fallacy is defined as a perceived susceptibility to underestimating schedules, costs, and risks while overestimating expected outcomes. Survey data from 165 technology startups in Tehran, Iran, were analyzed using partial least squares structural equation modeling. Planning fallacy was negatively associated with firm performance, while the lower-order path from AI maturity to performance was positive and significant. The interaction effect was negative and significant, indicating that the adverse association between planning fallacy and performance becomes stronger at higher levels of AI maturity. These findings position AI maturity as a contingent, double-edged capability whose value depends on disciplined and realistic planning. The study contributes to digital entrepreneurship by showing that AI maturity does not automatically neutralize planning bias; rather, its performance implications depend on alignment among AI capabilities, managerial attention, and venture planning routines.

1. Introduction

Artificial intelligence (AI) is increasingly embedded in the strategic and operational activities of technology startups. AI-related capabilities can strengthen data processing, automation, innovation, and decision support, thereby improving firms' capacity to respond to uncertain and rapidly changing markets (Chen et al., 2022; Giachino et al., 2025; Mishra et al., 2022). However, AI adoption alone does not guarantee superior outcomes. Its value depends on whether firms develop the governance, infrastructure, expertise, and organizational routines required to integrate AI into decision processes (Hansen et al., 2024; Khan et al., 2025; Lambert et al., 2026). Understanding AI performance therefore requires attention not only to technological capability but also to the managerial cognition through which AI-enabled information is interpreted and enacted.

This issue is especially salient in startups, where decision authority is concentrated, organizational routines are still developing, and resource slack is limited. Under these conditions, inaccurate planning assumptions can quickly affect hiring, investment, product development, and market-entry decisions. One particularly relevant cognitive bias is the planning fallacy: the tendency to underestimate the time, costs, and risks associated with future activities while overestimating expected benefits and opportunities (Buehler et al., 2010; Flyvbjerg, 2021). Reliance on such optimistic, inside-view forecasts can encourage excessive resource commitments and delay corrective action. Research on entrepreneurial cognition accordingly links extreme optimism and overconfidence to weaker venture performance and survival (Gudmundsson & Lechner, 2013; Hmieleski & Baron, 2009), while evidence from startups shows that persistent forecasting bias can distort investment, employment, and resource allocation (Konno, 2022).

The consequences of entrepreneurial bias are nevertheless not uniformly negative. Adomdza et al. (2016), for example, found that planning fallacy may facilitate fundraising by making entrepreneurs' venture projections more persuasive. This suggests that the implications of planning fallacy depend on the outcome and organizational conditions considered. Whereas bias may occasionally assist resource acquisition, its implications for operational performance are likely to depend on how unrealistic assumptions are translated into organizational commitments. The present study therefore focuses on top executives' perceived susceptibility to underestimating schedules, costs, and risks and examines its association with multidimensional firm performance.

Although the AI-performance and entrepreneurial-cognition literatures have developed rapidly, they remain weakly connected. Research on AI capability generally examines whether AI adoption or maturity improves performance, while cognitive research considers how entrepreneurs' biases shape venture decisions and outcomes. Less attention has been given to whether AI maturity changes the performance consequences of biased planning. This omission matters because AI systems do not independently determine organizational action. Their outputs must be interpreted, prioritized, and incorporated into planning and resource-allocation decisions by human actors. Consequently, mature AI capabilities may not automatically correct planning fallacy; instead, they may increase the organizational reach and performance consequences of the assumptions guiding their use.

To explain this interaction, the study integrates socio-technical systems theory with the attention-based view of the firm. Socio-technical systems theory conceptualizes AI maturity as an interdependent configuration of technical resources, governance arrangements, expertise, and organizational routines rather than as an isolated technological asset (Amanollahnejad et al., 2026). The attention-based view further proposes that organizational action depends on which issues and signals decision-makers notice, interpret, and prioritize (Ocasio, 1997). Together, these perspectives suggest that the value of AI maturity depends partly on the planning routines that direct managerial attention and resource commitments. Human–AI decision research supports this contingent view: decision-makers may reject, over-rely on, or selectively interpret algorithmic advice depending on trust, task characteristics, and consistency with prior beliefs (Jussupow et al., 2024; Keding & Meissner, 2021; Mahmud et al., 2022).

This study examines whether AI maturity moderates the relationship between planning fallacy and firm performance using survey data from 165 technology startups in Tehran, Iran. The setting is theoretically relevant because startups operating under substantial uncertainty and limited resource slack may be especially sensitive to inaccurate cost, schedule, and risk estimates. The hypotheses are tested using partial least squares structural equation modeling.

The study makes three contributions. First, it extends entrepreneurial-cognition research by examining planning fallacy as a performance-relevant bias in technology startups. Second, it contributes to digital entrepreneurship and AI-capability research by identifying AI maturity as a boundary condition that changes the strength of the planning fallacy–performance relationship. Third, it integrates socio-technical and attention-based explanations to show why AI maturity should not be treated as an

automatic corrective for managerial bias. The central argument is not that AI maturity is inherently detrimental, but that deeper AI integration may make startup performance more sensitive to the quality of top executives' planning assumptions.

2. Literature Review

2.1. Theoretical Foundations

This study integrates upper echelons theory, the attention-based view of the firm, and socio-technical systems theory, while drawing on entrepreneurial-cognition research to conceptualize planning fallacy. Upper echelons theory explains why the cognitive frames and judgments of founders and senior executives may become reflected in venture-level strategic choices and performance outcomes (Hambrick & Mason, 1984; Hambrick, 2007). The attention-based view explains how planning fallacy may shape the information, risks, and alternatives to which executives allocate attention, whereas socio-technical systems theory explains why the organizational consequences of those judgments may vary with the maturity and embeddedness of AI capabilities.

Socio-technical systems theory holds that organizational outcomes arise from the alignment of technical resources with social and organizational arrangements. In AI-enabled firms, these elements include data and computing infrastructure, analytical models, governance, expertise, decision rights, and operational routines (Amanollahnejad et al., 2026). AI maturity should therefore not be classified as a purely technical subsystem. Existing maturity frameworks conceptualize it as an institutionalized capability encompassing AI strategy and governance, data and infrastructure readiness, talent and routinized practices, and model-lifecycle management (Hansen et al., 2024; Khan et al., 2025). As these capabilities become embedded in organizational workflows, the assumptions guiding their deployment may influence a broader range of decisions and resource commitments.

The attention-based view explains how top executives' cognition enters this socio-technical configuration. Organizational action depends on the issues, information, and possible responses to which decision-makers allocate their limited attention (Ocasio, 1997). In startups, top executives planning assumptions can shape which AI-generated signals receive attention, how conflicting information is interpreted, and whether corrective action is taken. Planning fallacy may thus encourage decision-makers to privilege coherent, optimistic scenarios over base rates, implementation constraints, or adverse operational feedback.

This argument does not assume that biased top executives simply disregard AI outputs. Human–AI research indicates that decision-makers may display algorithm aversion, algorithm appreciation, selective reliance, or overreliance depending on the decision context (Jussupow et al., 2024; Keding & Meissner, 2021; Mahmud et al., 2022). These alternative pathways share a common implication: AI-enabled information does not operate independently of managerial interpretation. Socio-technical systems theory identifies the interdependent capability configuration through which AI is deployed, while

the attention-based view explains how top executives planning assumptions shape its use. Their integration therefore supports the proposition that AI maturity may alter the strength of the association between planning fallacy and firm performance, particularly in resource-constrained startups.

2.2. Planning Fallacy and Entrepreneurial Outcomes

The planning fallacy is a forecasting bias in which decision-makers underestimate the time required to complete future tasks despite relevant experience with comparable activities (Buehler et al., 2010). Its broader, “writ-large” formulation extends this tendency to the underestimation of costs, schedules, and risks and the overestimation of benefits and opportunities (Flyvbjerg, 2021). The bias arises principally from reliance on the inside view: planners construct a coherent scenario around the focal project while giving insufficient weight to base rates, prior overruns, and the range of outcomes observed in comparable cases (Buehler et al., 2010; Kahneman & Lovallo, 1993). The resulting estimates tend to resemble favorable scenarios more closely than realistic distributions of possible outcomes.

Planning fallacy should be distinguished from both business planning and deliberate forecast manipulation. Planning itself can improve new-venture performance by clarifying objectives, coordinating action, and supporting employment growth, although its value varies across venture profiles and contexts (Burke et al., 2010). The theoretical concern in this study is therefore not the use of plans, but the systematic bias embedded in their assumptions. Similarly, knowingly presenting inflated forecasts for strategic purposes constitutes strategic misrepresentation rather than a nondeliberate cognitive fallacy (Flyvbjerg, 2021). The present study focuses on perceived susceptibility to biased underestimation and overestimation, not intentional deception.

Such biases are consequential in entrepreneurship because top executives make interdependent decisions concerning investment, staffing, product development, and market entry under considerable uncertainty. Persistent forecasting bias can move capital investment and employment away from appropriate levels and impede efficient resource allocation (Konno, 2022). Related research also links excessive entrepreneurial optimism and overconfidence to weaker growth or survival by encouraging under-resourcing, insufficient risk precautions, and delayed responses to unfavorable information (Gudmundsson & Lechner, 2013; Hmieleski & Baron, 2009). These consequences may be particularly important in young firms, where limited slack reduces the capacity to absorb schedule extensions, cost overruns, or benefit shortfalls.

The effects of cognitive bias are nevertheless outcome-dependent. Adomdza et al. (2016) found that planning fallacy can increase entrepreneurial funding and may indirectly support venture performance through greater self-investment and investor financing. Bias may therefore facilitate commitment or persuasion in resource-acquisition settings, even when the underlying premises are inaccurate. This evidence cautions against treating planning fallacy as uniformly detrimental. The present study concerns a different pathway: the relationship between top executives’ biased planning tendencies and multidimensional operating performance. In this setting, underestimated implementation demands and

overestimated outcomes are expected to weaken performance by producing mismatches between planned commitments and the resources, time, and risks actually encountered.

2.3. AI Maturity as an Organizational Capability

AI maturity refers to the extent to which a firm has institutionalized AI-related capabilities so that they are consistently embedded in recurring decision and operational processes. It differs from isolated AI adoption or experimentation because it reflects an overarching organizational state of AI institutionalization. Existing maturity frameworks commonly emphasize strategy and governance, data and infrastructure readiness, technical and managerial expertise, and model-development and lifecycle practices (Hansen et al., 2024; Khan et al., 2025; Lichtenthaler, 2020). As firms become more mature, they are expected to exhibit coordinated development across these organizational manifestations rather than merely possess isolated algorithms or technologies.

The performance value of AI maturity depends on how effectively this maturity state is embedded in organizational routines. Firms with more institutionalized AI capabilities are expected to display stronger governance, more developed infrastructure, greater expertise, and more systematic practices for translating model outputs into decisions. When these manifestations develop coherently, AI maturity can strengthen information processing, operational coordination, innovation, and managerial responsiveness (Chen et al., 2022; Giachino et al., 2025; Mishra et al., 2022). Conversely, the absence of reliable data, appropriate skills, governance mechanisms, or decision routines may limit the performance value of AI-related investments (Amanollahnejad et al., 2026; Lambert et al., 2026).

Importantly, deeper AI institutionalization may also increase the organizational reach of the assumptions embedded in planning and decision processes. As AI-supported routines become more widely used, managerial priorities may be translated into a larger number of resource allocations, forecasts, and operational actions. Mature AI capabilities can therefore improve the consistency and speed of organizational execution, but they may also increase the consequences of poor assumptions when implementation choices are based on underestimated costs, unrealistic schedules, or insufficiently assessed risks. Recent studies similarly suggest that the value of AI depends on strategic focus, organizational learning, governance, and complementary managerial capabilities rather than on adoption intensity alone (Ayoub & Sopuru, 2026; Hong et al., 2026; Lambert et al., 2026).

This contingent perspective is central to the present study. AI maturity is not theorized as inherently harmful or as an automatic remedy for cognitive bias. Instead, it represents an organizational state that may alter how strongly top executives' planning assumptions are translated into firm-level outcomes. In startups, where decision authority is concentrated and implementation capacity is limited, AI maturity may therefore shape the performance consequences of planning fallacy.

3. Hypotheses Development

3.1. Planning Fallacy and Firm Performance

Planning fallacy can impair firm performance by distorting the assumptions on which entrepreneurial decisions are based. When top executives underestimate implementation time, costs, and risks or overestimate expected benefits, resource commitments may become misaligned with the demands ultimately encountered. These errors can affect product-development schedules, staffing, financing needs, and market-entry decisions, with potentially cumulative consequences across interdependent startup activities (Buehler et al., 2010; Flyvbjerg, 2021; Konno, 2022).

The expected relationship is not based on the premise that planning itself is detrimental. Formal planning can improve coordination and support new-venture development when it is grounded in realistic assumptions (Burke et al., 2010). The concern is instead the systematic bias embedded in planning estimates. In resource-constrained firms, underestimated requirements may create funding gaps, operational delays, and premature scaling, while overestimated benefits may sustain commitments to weak courses of action. Related research links excessive entrepreneurial optimism and overconfidence to lower growth and survival, particularly when biased judgments reduce responsiveness to unfavorable information (Gudmundsson & Lechner, 2013; Hmieleski & Baron, 2009).

Although planning fallacy may occasionally aid persuasion or resource acquisition, such benefits do not necessarily translate into stronger operating outcomes (Adomdza et al., 2016). For firm performance, persistent discrepancies between planning assumptions and implementation demands are expected to weaken the venture's ability to allocate resources efficiently and achieve financial, market, innovation, and customer-related objectives. Accordingly:

H1. Planning fallacy is negatively related to firm performance.

3.2. The Moderating Role of AI Maturity

AI maturity may change the strength of the relationship between planning fallacy and firm performance because it affects how extensively managerial assumptions are translated into organizational action. In firms with mature AI capabilities, data infrastructures, governance routines, technical expertise, and model-management practices are more deeply embedded in recurring decisions and workflows (Hansen et al., 2024; Khan et al., 2025). Such integration can improve information processing and execution, but it can also broaden the organizational consequences of the planning assumptions that guide AI-enabled priorities and resource commitments.

Socio-technical systems theory suggests that the value of AI maturity depends on alignment between AI-related capabilities and the managerial routines through which they are governed and used (Amanollahnejad et al., 2026). When top executives' plans are based on underestimated implementation demands or overstated expected outcomes, mature AI capabilities may enable those assumptions to be enacted more rapidly or across a wider set of activities. The issue is therefore not that AI maturity is intrinsically harmful, but that deeper capability integration may increase the firm-level consequences of unrealistic planning.

The attention-based view further explains how this interaction may arise. top executives influence which information is prioritized, how conflicting signals are interpreted, and when plans are revised (Ocasio, 1997). Planning fallacy may direct attention toward coherent, optimistic scenarios and away from base rates, operational constraints, or adverse feedback. AI-generated information does not necessarily eliminate this tendency. Decision-makers may discount algorithmic advice, rely on it excessively, or interpret it selectively in ways that remain consistent with prior expectations (Jussupow et al., 2024; Keding & Meissner, 2021; Mahmud et al., 2022).

These mechanisms are not directly measured in the present study and should therefore be understood as theoretically plausible pathways rather than demonstrated mediators. Nevertheless, they converge on the expectation that the performance implications of biased planning will become more pronounced as AI capabilities are more deeply institutionalized. In startups, mature AI systems may increase the scale, speed, and coordination of decisions shaped by top executives' assumptions, thereby strengthening the negative association between planning fallacy and performance. Accordingly:

H2. AI maturity moderates the relationship between planning fallacy and firm performance such that the negative association becomes stronger at higher levels of AI maturity.

Figure 1 presents the proposed relationships among planning fallacy, AI maturity, and firm performance.

4. Methodology

4.1. Sample and Data Collection

A cross-sectional survey was conducted among technology startups operating in Tehran, Iran. The startup was the unit of analysis, and respondents were founders, chief executive officers, or managing directors occupying upper-echelon positions and directly involved in the venture's strategic planning and AI-related decisions. Consistent with upper echelons theory, these respondents were considered appropriate key informants because their cognitive interpretations and strategic judgments are likely to be reflected in venture-level choices and outcomes.

A purposive sampling approach was used to identify startups with fewer than 100 employees that were actively adopting, developing, or using AI-related applications. Data were collected through a structured online questionnaire. After screening for completeness and eligibility, 165 valid startup-level responses were retained. The sample included firms operating in e-commerce, software-as-a-service, fintech, digital logistics, and related technology sectors.

As a supplementary sample-adequacy check, the minimum-sample-size guidelines reported by Hair et al. (2022) were considered. The smallest absolute structural path coefficient in the estimated model was .232, which falls within the .21–.30 range. At a 5% significance level, the corresponding minimum sample size is 69 observations. The final sample of 165 therefore exceeded this benchmark, supporting the adequacy of the sample for estimating the proposed structural relationships.

Participation was voluntary, respondent confidentiality was assured, and informed consent was obtained before questionnaire completion. The questionnaire was originally developed in English and then translated into Persian and reviewed by bilingual domain experts to ensure conceptual and linguistic equivalence before administration. To reduce common method concerns, predictor and outcome measures were placed in separate questionnaire sections, item wording was kept clear and neutral, and question order was counterbalanced. In addition, the predictor and outcome constructs referred to different temporal frames – planning fallacy to deviations experienced in prior projects and firm performance to the venture’s current standing relative to competitors – which provides a degree of psychological separation between the measures. These procedures were intended to reduce, rather than eliminate, the possibility of common method bias.

4.2. Measures

Planning fallacy, AI maturity, and firm performance were modeled as reflective constructs. A reflective specification was appropriate because, within each construct, the indicators were expected to share a common underlying cause and to be interchangeable manifestations of it rather than distinct causal facets. All measures were adapted from established literature and contextualized for technology startups. Table 1 summarizes their operationalization.

Table 1
Operationalization of the study variables

Construct	Operationalization	Measurement source
Planning fallacy	Perceived susceptibility to underestimating schedules, costs, and unexpected risks and to overestimating anticipated benefits and opportunities	Four items developed based on Flyvbjerg’s (2021) conceptualization
AI maturity	Overall degree to which AI capabilities are consistently embedded, routinized, and institutionalized in the startup’s core workflows, as reflected in AI strategy and governance, data and infrastructure readiness, talent and routinized practices, and model-lifecycle management	Four reflective indicators forming an abbreviated adaptation of Khan et al. (2025)
Firm performance	Performance relative to principal competitors across growth, financial, market, innovation, and customer-related dimensions	Ten seven-point comparative items adapted from Stam and Elfring (2008)
Annual sales growth	Percentage change in annual sales	Single self-reported numerical indicator used for criterion-related validation

Planning fallacy was assessed using four items developed from Flyvbjerg’s (2021) writ-large conceptualization, with each item corresponding to one of its constituent dimensions: underestimation of costs, underestimation of schedules, underestimation of risks, and overestimation of expected benefits (see Appendix A). Because the planning fallacy is defined by the persistence of underestimation

despite prior experience with comparable projects (Buehler et al., 2010; Kahneman & Lovallo, 1993), the items asked informants to assess the recurrent underestimation of costs, schedules, and risks and the overestimation of benefits across their prior projects. Because the items reflect respondents' assessments of past project deviations rather than observed differences between original forecasts and realized outcomes, the construct represents a perceived susceptibility to the planning fallacy rather than an objective measure of forecasting error.

AI maturity was measured using four organization-level indicators adapted from Khan et al. (2025). Each indicator captured one of the four content domains of operations-anchored AI capability identified by Khan et al. (2025): AI strategy and governance (e.g., an AI roadmap, dedicated oversight, and ethics or risk protocols); data and infrastructure readiness (e.g., data integration, pipeline scalability, and real-time connectivity); talent and routinized practices (e.g., an AI-skilled workforce, established development standards, and internal training); and model-lifecycle management (e.g., deployment, monitoring, CI/CD, and feedback loops). The full item wording is reported in Appendix A. Khan et al. (2025) conceptualize AI maturity as the depth, consistency, and institutionalization of AI capabilities embedded in organizational workflows and assess it through multi-item measures across these domains. The present study uses an abbreviated four-item adaptation suited to the startup context.

AI maturity was specified reflectively because it was conceptualized as the overall degree to which AI capabilities are institutionalized in the startup — a single underlying property that firms exhibit to a greater or lesser extent — such that its manifestations across the four domains are expected to covary as maturity increases (Coltman et al., 2008). This interpretation is consistent with the high internal consistency and shared variance observed among the four indicators (see Table 2).

Firm performance was measured using ten items adapted from Stam and Elfring (2008). Respondents compared their firms with their principal competitors across ten dimensions: sales growth, employment growth, market share, gross profits, net profit margin, innovation in products and services, speed in developing new products and services, quality of products and services, cost control, and customer satisfaction. Each item was rated on a seven-point scale ranging from 1 ("much worse") to 7 ("much better"). Annual sales growth was additionally reported as a percentage and used as a criterion-related validity indicator. Because this percentage was self-reported by the same respondent, it was not treated as independently verified objective data.

4.3. Analytical Strategy

The model was estimated using partial least squares structural equation modeling in SmartPLS 3. PLS-SEM was suitable for evaluating the proposed moderation relationship and the model's explanatory and predictive performance with a sample of 165 observations (Dash & Paul, 2021; Hair et al., 2019, 2022).

The reflective measurement model was assessed using indicator loadings, Cronbach's alpha, rho_A, composite reliability, and average variance extracted. Discriminant validity was examined using the heterotrait–monotrait ratio of correlations (Henseler et al., 2015).

The structural model included the lower-order paths from planning fallacy and AI maturity to firm performance and their interaction term. The AI maturity–performance path was included as a constituent term of the moderation specification rather than as a separate hypothesized relationship. Structural collinearity was assessed using inner VIF values, and path significance was evaluated through bootstrapping with 5,000 subsamples. Explanatory power was assessed using R^2 , while effect sizes were evaluated using f^2 .

Out-of-sample predictive performance was assessed using PLSpredict with 10 folds and 10 repetitions. Prediction errors from the PLS-SEM model were compared with those of a linear-model benchmark following Shmueli et al. (2019). The relationship between the latent performance construct and percentage sales growth was examined separately as evidence of criterion-related validity.

5. Results

5.1. Measurement Model Evaluation

The reflective measurement model was evaluated using indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. As shown in Table 2, all indicator loadings exceeded .86. Cronbach’s alpha, rho_A, and composite reliability were above .70 for all constructs, while average variance extracted exceeded .50. These results support indicator reliability, internal consistency, and convergent validity.

Table 2. Reliability and convergent-validity assessment

Construct	Items	Loading range	Cronbach’s α	rho_A	Composite reliability	AVE
AI maturity	4	.869–.881	.898	.906	.929	.766
Planning fallacy	4	.867–.910	.908	.928	.935	.782
Firm performance	10	.862–.899	.968	.970	.972	.779

Note. AVE = average variance extracted.

Discriminant validity was assessed using the heterotrait–monotrait ratio. All HTMT values were below the conservative threshold of .85, as reported in Table 3, indicating that the three constructs were empirically distinct.

Table 3. Heterotrait–monotrait ratios

Construct	1	2	3
1. AI maturity	—		
2. Planning fallacy	.067	—	
3. Firm performance	.448	.311	—

As a supplementary criterion-related validity check, the latent performance construct was examined in relation to annual sales growth measured as a percentage. The relationship was positive and significant ($\beta=.350$, $SE=.062$, $t=5.670$, $p<.001$). This result indicates that the comparative performance measure was meaningfully associated with a more concrete numerical growth indicator. Because sales growth was self-reported by the same respondent, however, this analysis should not be interpreted as independent validation or as a formal test of common method bias.

5.2. Structural Model and Hypothesis Testing

Before testing the hypotheses, collinearity among the predictors of firm performance was examined using inner VIF values. The VIF values for AI maturity, planning fallacy, and their interaction were 1.014, 1.019, and 1.024, respectively, indicating that structural collinearity was not a concern.

The model explained 30.3% of the variance in firm performance ($R^2=.303$; adjusted $R^2=.291$). Planning fallacy was negatively associated with firm performance ($\beta=-.249$, $t=3.959$, $p<.001$), supporting H1. AI maturity, included as a lower-order constituent term of the moderation model, was positively associated with firm performance ($\beta=.430$, $t=7.452$, $p<.001$). The interaction between planning fallacy and AI maturity was negative and significant ($\beta=-.232$, $t=3.582$, $p<.001$), supporting H2. The negative interaction coefficient indicates that the association between planning fallacy and firm performance becomes more negative as AI maturity increases.

The effect-size results show that AI maturity had a medium effect on firm performance ($f^2=.261$), whereas planning fallacy ($f^2=.087$) and the interaction term ($f^2=.067$) had small effects. Figure 2 presents the standardized path coefficients obtained from the PLS algorithm, while Figure 3 reports the corresponding bootstrapping t-statistics. Table 4 summarizes the estimated structural paths, their statistical significance, corresponding effect sizes, and hypothesis decisions.

Table 4. Structural-model results

Structural relationship	β	t	p	f^2	Effect size	Decision
Planning fallacy → Firm performance	-.249	3.959	<.001	.087	Small	H1 supported
Planning fallacy × AI maturity → Firm performance	-.232	3.582	<.001	.067	Small	H2 supported

Note. Significance was assessed using 5,000 bootstrap subsamples. Effect-size interpretation follows the conventional f^2 thresholds of .02, .15, and .35 for small, medium, and large effects, respectively.

To examine the form of the moderation, a simple slope analysis was conducted by plotting the relationship between planning fallacy and firm performance at the mean and at one standard deviation below and above the mean of AI maturity. As shown in Figure 4, the negative relationship becomes steeper as AI maturity increases. This pattern is consistent with the negative interaction coefficient and indicates that the adverse association between planning fallacy and firm performance is stronger at higher levels of AI maturity.

5.3. Out-of-Sample Predictive Performance

Out-of-sample predictive performance was evaluated using PLSpredict with 10 folds and 10 repetitions. The Q^2_{predict} values were positive for all ten firm-performance indicators, indicating that the model outperformed a naïve prediction based on indicator means.

The PLS-SEM model produced lower root mean square error and mean absolute error values than the linear-model benchmark for nine of the ten indicators. Because the PLS-SEM prediction errors were lower than those of the linear-model benchmark for the majority, but not all, of the indicators, the model demonstrates medium out-of-sample predictive power under the assessment criteria proposed by Shmueli et al. (2019).

6. Discussion

The findings show that planning fallacy is negatively associated with firm performance and that this relationship becomes more negative as AI maturity increases. The lower-order path from AI maturity to performance was positive, indicating that mature AI capabilities are associated with stronger performance on average. The interaction therefore should not be interpreted as evidence that AI maturity is inherently detrimental. Rather, the results suggest that AI maturity increases the performance consequences of the planning assumptions through which AI-enabled resources are deployed.

The negative association between planning fallacy and performance is consistent with entrepreneurial-cognition research showing that optimistic forecasting can distort resource allocation, delay corrective action, and weaken venture outcomes (Gudmundsson & Lechner, 2013; Hmieleski & Baron, 2009; Konno, 2022). In startups, underestimated schedules, costs, and risks can be especially consequential because limited resource slack reduces the firm's capacity to absorb planning overruns. At the same time, this result should not be generalized to all outcomes of entrepreneurial bias. Planning fallacy may occasionally support commitment or resource acquisition, including fundraising (Adomdza et al., 2016). The present findings concern multidimensional operating performance rather than the persuasive or motivational benefits of optimistic projections.

The moderation result extends this literature by identifying AI maturity as a boundary condition of the planning fallacy–performance relationship. The simple slope pattern indicates that the negative association becomes steeper at higher levels of AI maturity, although the significance of individual conditional slopes was not tested. This pattern is consistent with the view that mature AI capabilities broaden the organizational reach of managerial assumptions. When AI-related governance, infrastructure, expertise, and model-management routines are deeply embedded in operations, planning assumptions may inform a wider range of forecasts, priorities, and resource commitments. Consequently, unrealistic assumptions may have more extensive performance implications.

Although the interaction term produced a small effect size by conventional benchmarks ($f^2 = .067$), small interaction effects are common in field research and can be practically meaningful, particularly for outcomes such as firm performance that are shaped by many concurrent factors (Aguinis et al., 2005). The simple-slope analysis illustrates this practical relevance: the association between planning fallacy and performance is substantially steeper at higher levels of AI maturity than at lower levels, indicating that the moderating role of AI maturity is not merely statistically detectable but consequential for how strongly biased planning translates into performance differences.

Socio-technical systems theory helps explain this contingency. AI maturity represents an interdependent configuration of technical and organizational capabilities whose value depends on alignment with the routines guiding their use (Amanollahnejad et al., 2026). The findings are therefore more consistent with socio-technical contingency than with technological determinism. Mature AI capabilities may support stronger performance, but their value is not independent of the quality of managerial planning. This interpretation also aligns with evidence that AI-related performance gains depend on complementary governance, skills, strategic focus, and organizational practices (Hong et al., 2026; Lambert et al., 2026).

The attention-based view provides a complementary explanation. Top executives-level planning assumptions can influence which operational signals receive attention, how contradictory information is interpreted, and when corrective action is initiated (Ocasio, 1997). Planning fallacy may lead top executives to privilege internally coherent, optimistic scenarios over base rates, implementation constraints, or unfavorable feedback. Human–AI decision research suggests that algorithmic information does not automatically correct such tendencies: decision-makers may discount, over-rely on, or selectively interpret AI-supported recommendations depending on trust and decision context (Jussupow et al., 2024; Keding & Meissner, 2021; Mahmud et al., 2022). These processes were not directly measured in the present study, so they should be treated as plausible explanations rather than demonstrated mediators.

6.1. Theoretical Implications

The study contributes to entrepreneurial-cognition research by positioning planning fallacy as a performance-relevant bias whose consequences depend on the organizational context in which planning assumptions are enacted. Rather than treating cognitive bias as an isolated individual characteristic, the

findings suggest that its firm-level implications may depend on the capabilities through which managerial decisions are implemented.

The study also contributes to AI-capability research by presenting AI maturity as a contingent organizational capability. The positive lower-order association indicates that AI maturity is positively associated with performance on average, while the negative interaction suggests that its performance value is more dependent on realistic planning. The theoretical contribution is therefore not that AI maturity becomes a liability, but that deeper AI integration may raise the performance stakes of planning quality.

Finally, the study connects socio-technical systems theory with the attention-based view. Socio-technical systems theory explains the interdependence between AI capabilities and organizational routines, while the attention-based view explains how top executives' planning assumptions may shape the interpretation and enactment of AI-enabled information. Their integration offers a cross-level explanation of how individual cognition may interact with organizational AI maturity to influence firm performance.

6.2. Practical Implications

The findings suggest that startups should not treat investment in AI maturity as a substitute for disciplined planning. As AI capabilities become more deeply embedded in operations, firms should strengthen planning routines that incorporate historical evidence, comparable-project outcomes, implementation risks, and explicit cost and schedule contingencies. Outside-view forecasting and reference-class information may help counter excessive reliance on optimistic project narratives (Buehler et al., 2010; Flyvbjerg, 2021).

AI governance should also include mechanisms for challenging the assumptions underlying AI-enabled decisions. Independent review of major forecasts, pre-mortem analysis, staged resource commitments, and explicit documentation of model assumptions may reduce the risk that AI systems are used to reinforce unrealistic plans. Investors and accelerator managers should similarly assess not only the sophistication of a startup's AI capabilities but also the quality of the planning and governance routines through which those capabilities are deployed.

6.3. Limitations and Future Research

Several limitations qualify the findings. First, the cross-sectional design does not permit causal inference or observation of how planning bias and AI maturity evolve over time. Longitudinal research could examine whether changes in AI maturity alter the consequences of planning fallacy across venture-development stages.

Second, planning fallacy was measured as a perceived susceptibility based on informants' assessments of past project deviations, rather than as the observed difference between original forecasts and realized outcomes. Moreover, because the planning-fallacy items asked founders to acknowledge cost overruns, delays, and unmet expectations in their own past projects, social-desirability pressures would tend to

bias these self-assessments downward; the significant negative associations reported here may therefore represent conservative estimates. Future studies should collect original schedule, cost, and benefit forecasts and compare them with subsequent results.

Third, the data were obtained from single key informants. Although percentage sales growth provided supplementary criterion-related validity evidence, it was also self-reported and did not eliminate common method concerns.

Fourth, the proposed attention and socio-technical mechanisms were not directly measured. Future research should examine attention allocation, algorithm reliance, AI-output interpretation, and socio-technical alignment as mediators.

Fifth, the sample comprised technology startups in Tehran, Iran. While this restricts statistical generalizability, it also situates the study in an emerging-market entrepreneurial context that remains underexamined in the AI-capability and entrepreneurial-cognition literatures, where evidence is drawn predominantly from developed economies. Because resource constraints, institutional uncertainty, and volatility are typically more pronounced in such settings, they offer a theoretically informative context in which the performance consequences of planning fallacy may be especially salient. Comparative research across institutional environments, economic conditions, and more decentralized organizations would nonetheless help establish the boundary conditions and cross-context robustness of the observed interaction.

Finally, AI maturity was modeled reflectively through an abbreviated adaptation of Khan et al. (2025). Although the reflective specification was appropriate for the level-based conceptualization adopted here, future studies could examine formative or higher-order configurational specifications that emphasize the distinct contribution of each capability domain.

7. Conclusion

This study examined whether AI maturity changes the relationship between top executives' planning fallacy and firm performance in technology startups. Using data from 165 startups in Tehran, the findings show that planning fallacy is negatively associated with firm performance and that this association becomes more negative as AI maturity increases. The lower-order path from AI maturity to performance was positive, indicating that AI maturity is positively associated with performance at the mean level of planning fallacy.

The central implication is that AI maturity does not operate independently of managerial cognition. As AI-related governance, infrastructure, expertise, and model-management routines become more deeply embedded in organizational processes, the assumptions guiding their use may have broader performance consequences. Mature AI capabilities can support stronger performance, but they do not automatically correct unrealistic planning. Instead, their value appears to depend partly on whether top executives assess schedules, costs, risks, and expected outcomes realistically.

By integrating socio-technical systems theory with the attention-based view, the study offers a contingent account of AI maturity in entrepreneurship. It shows that the performance implications of top executives cognition may depend on the organizational capabilities through which planning decisions are enacted. For practitioners, the findings indicate that investments in AI maturity should be accompanied by planning and governance routines that challenge optimistic assumptions, incorporate external evidence, and enable timely revision of strategic commitments.

Because the study is cross-sectional and relies primarily on perceptual measures, the findings should be interpreted as associations rather than causal effects. Nevertheless, they suggest that the performance value of AI maturity depends not only on technological and organizational readiness, but also on the quality of the planning judgments directing its use.

Declarations

Author Contribution

M.P. developed the conceptual framework and theoretical foundations, designed the research, and supervised the study. M.A. conducted the research, performed the PLS-SEM analysis using SmartPLS, interpreted the results, and drafted the manuscript. Y.S. contributed to the development of the conceptual framework and theoretical foundations. J.M. provided methodological and scholarly consultation and critically reviewed and revised the manuscript. All authors reviewed and approved the final version of the manuscript.

Data Availability

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy issues.

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Figures

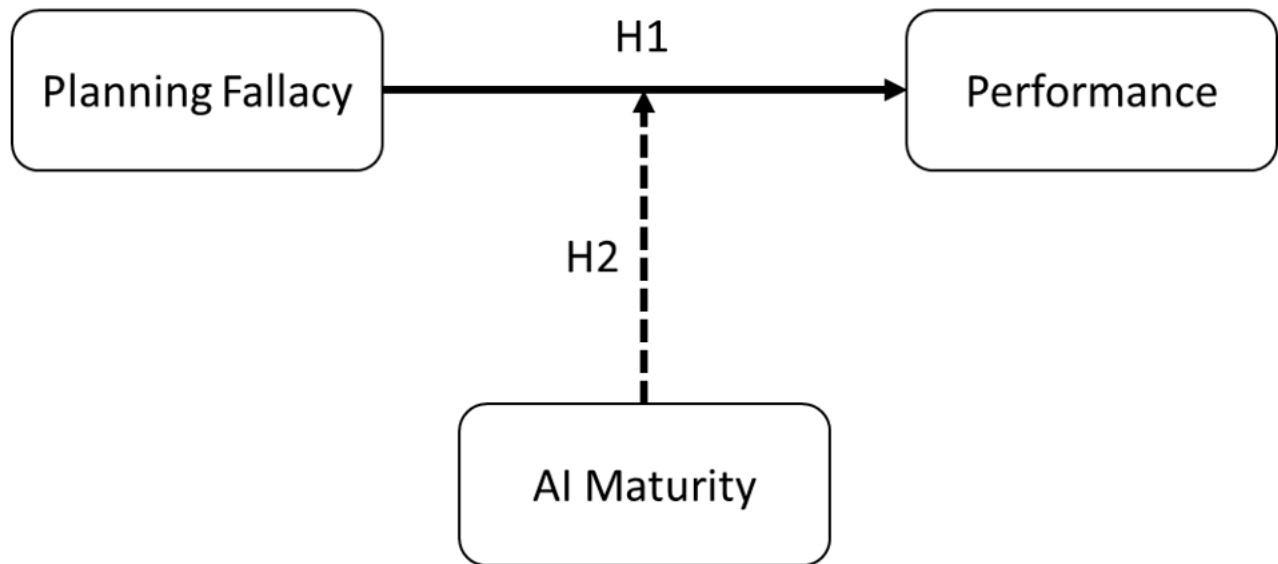


Figure 1

Conceptual framework of the study

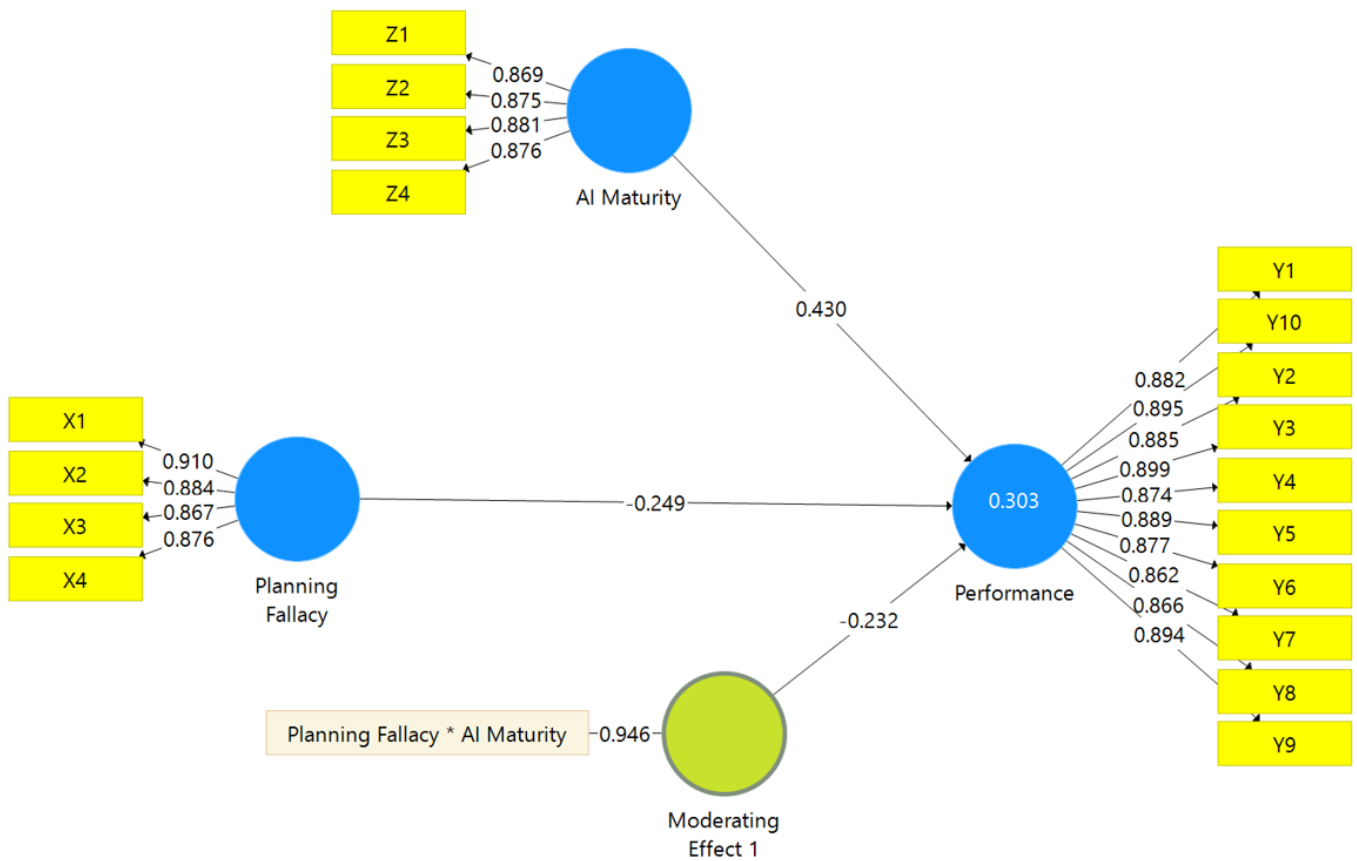


Figure 2

PLS algorithm results for the structural model.

Note. Values on the structural paths represent standardized path coefficients, and the value within the endogenous construct represents R^2 .

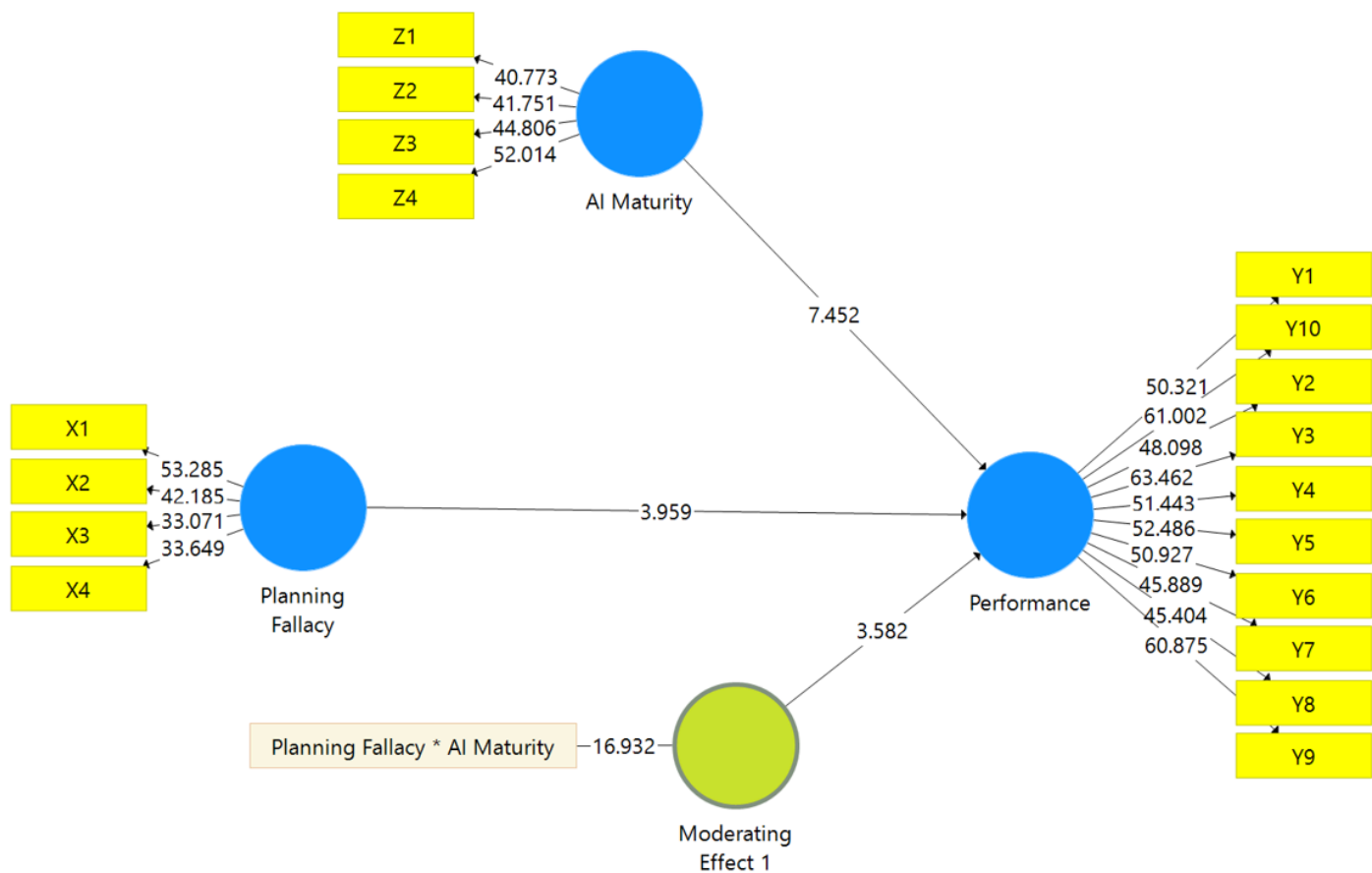


Figure 3

Bootstrapping results for the structural model.

Note. Values on the structural paths represent bootstrapping t-statistics based on 5,000 subsamples.

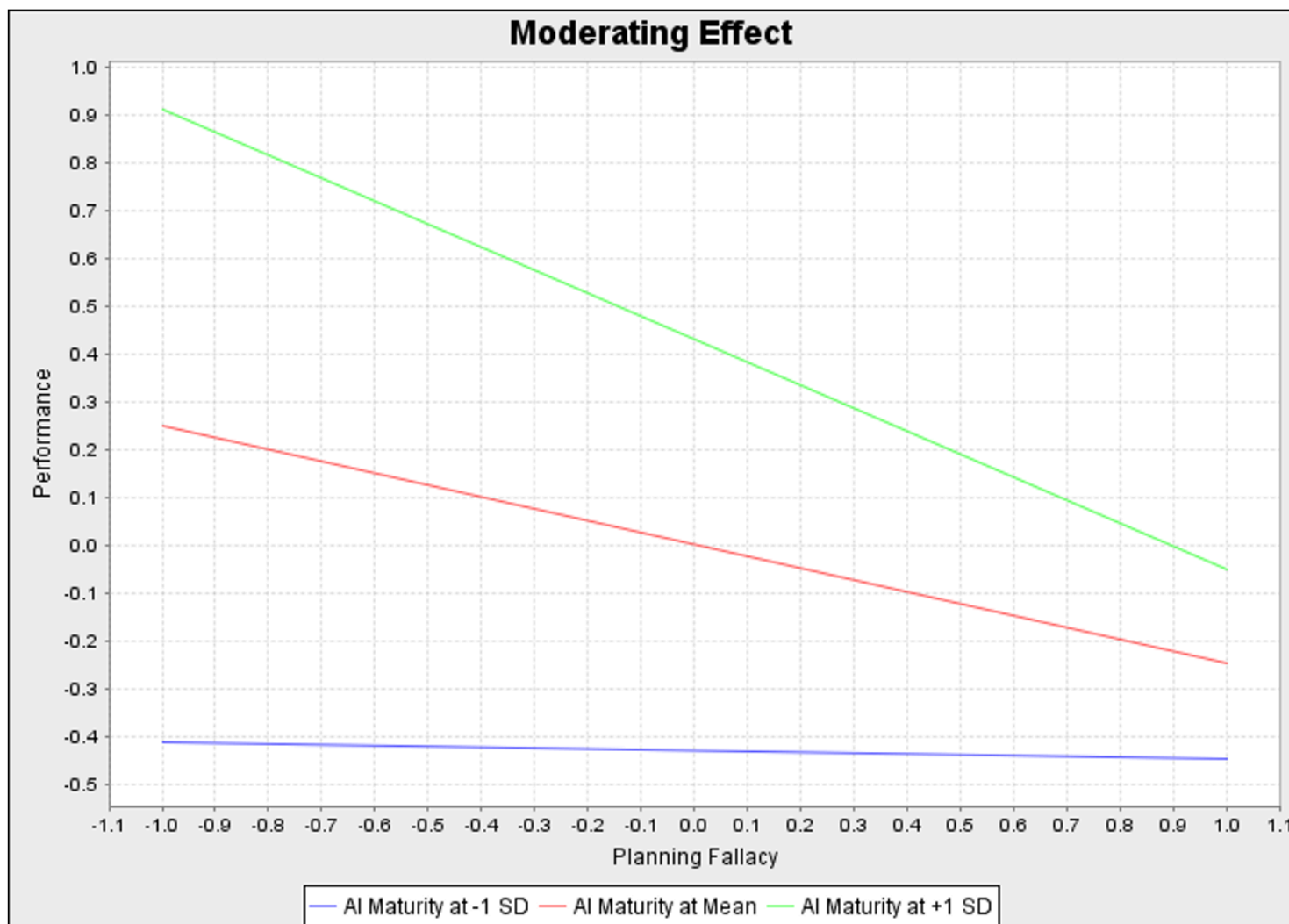


Figure 4

Simple slope analysis of the moderating effect of AI maturity on the relationship between planning fallacy and firm performance.

Supplementary Files

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- [AppendixA.docx](#)