

The Role of Facilitating Conditions and Trust in Driving Predictive AI Risk Adoption: A Project Management Perspective

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Abstract

Artificial intelligence (AI) risk tools that predict future events assist project managers in preventing delays, cost overruns, and quality difficulties. This does not stop a lot of businesses from ignoring their availability. In this study, we look at how two factors—trust in AI (TR) and enabling conditions (FC)—effect the uptake of AD, or predictive AI risk instruments, under project management. The study used multiple regression and correlation analysis to draw conclusions from a quantitative cross-sectional survey of 220 project experts. Adoption is positively and significantly impacted by both trust and enabling conditions, with trust mediating in part the influence of enabling factors. The article comes to the conclusion that in order for project teams to regularly utilize predictive risk technologies, companies need to establish both technical support and confidence in AI outputs.

Keywords: predictive AI, project risk management, facilitating conditions, trust, technology adoption, UTAUT

1. Introduction

1.1 Background

A project's outcome is inherently unpredictable. As needs evolve, timelines fall and finances balloon. Accordingly, the Project Management Institute (PMI) identifies risk management as a fundamental aspect of project management education and practice (2021). For a long time, risk management relied on workshops, expert opinion, and risk registers. The methods are helpful, but they are sluggish, open to subjective interpretation, and frequently only updated during review meetings. Another approach is provided by predictive AI. Machine learning models can be trained using both historical project data and real-time information, including task progress, resource utilization, and communication patterns. They will be able to evaluate the likelihood of a delay or overrun and promptly notify the team. The use of such instruments has the potential to make data-driven, continuous, and opinion-less risk management a reality. Having technology at your disposal is different from actually using it. A lot of companies spend money on AI systems that never get deployed or are relegated to reporting purposes. Scientists have known for a long time that individuals will embrace a new system if they think it will be helpful and simple to use (Davis, 1989) and if their company will back them (Venkatesh et al., 2003). There is another significant factor in AI. AI provides recommendations that are difficult to verify, therefore it is up to the user to choose how much weight to assign to them. It is confidence that will determine this choice (Lee & See, 2004).

1.2 Problem Statement

The application of predictive AI by project managers and teams is crucial if organizations are to reap the benefits of investing in such technology for project risk. Perceived utility and usability have been the primary foci of prior research. In project management contexts, there is an even smaller body of research that examines enabling factors like faith in AI, management assistance, data quality, and infrastructure. This chasm makes it difficult for businesses to decide whether to put money into trust-building efforts, better processes and support, or both.

1.3 Significance of the Study

By studying trust and facilitating conditions in a single model for a project management setting, the study advances theory. It advances practice by highlighting the most important issues for technology suppliers, PMO directors, and project sponsors.

2. Literature Review

Risk Management in Projects

Uncertain events can have both good and negative effects on project objectives, and this is known as project risk. Risk identification, analysis, response, and monitoring are all part of standard practice (PMI, 2021). Risk planning increases the likelihood of a project's success, according to research by *Zwikael and Ahn (2011)*; however, the extent to which this is true varies conditional on the industry and country in question. This demonstrates that the quantity of risk work is irrelevant to its quality.

Human estimations are the backbone of traditional systems like risk registries and probability-impact matrices. These estimations are prone to bias and are frequently considered after the fact, when they are no longer relevant. Project managers are interested in data-driven prediction because it helps them overcome this shortcoming.

Predictive AI for Project Risk

Predictive AI refers to models that learn patterns from historical and live data in order to forecast future outcomes. In projects, such models are used to predict schedule delay, cost overrun, resource conflicts and defects. A key feature is that these tools often work as "black boxes": the user sees the prediction but not always the reason for it. This makes the user's willingness to rely on the tool a human and organizational issue as well as a technical one.

Technology Adoption Theories

According to Davis (1989), the Technology Acceptance Model (TAM) elucidates adoption by way of perceived utility and perceived simplicity of use. *Ajzen (1991)* expanded the Theory of Planned Behavior to include perceptions of agency, social norms, and attitudes. *Venkatesh et al. (2003)* collected previous theories to develop the Unified Theory of Acceptance and Use of Technology (UTAUT), which posits four primary factors: social impact, enabling conditions, performance expectancy, and effort expectancy. According to *Venkatesh et al. (2012)*, UTAUT2 is an expanded version that incorporates hedonic incentive, price value, and habit.

Facilitating Conditions

The presence of organizational and technical assistance that aids persons in making effective use of technology is known as facilitating conditions. Resources, infrastructure, and support required to employ technology are all considered enabling factors within the UTAUT paradigm (*Vinkatesh et al., 2003*). *Taylor and Todd (1995)* and *Thompson et al. (1991)* also addressed similar ideas. Proper training, technical assistance, clear organizational policies, access to high-quality project data, integration of AI tools with existing project management software, and other enabling factors are essential in AI-based risk analytics. Encouraging project managers to confidently employ AI tools also requires support from higher management. Even the most sophisticated AI systems can be useless without these facilities. Users' faith in the technology may take a hit, for instance, if risk projections were based on low-quality project data. So, to improve the successful implementation of AI risk analytics in project management, strong supporting conditions are necessary.

Trust in AI

To trust someone or something is to have faith that they will carry out their duties accurately and consistently. *Mayer et al. (1995)* propose that honesty, kindness, and competence are the pillars upon which trust rests. A competent, helpful, and trustworthy individual or system should meet these requirements. Trust in automated systems ought to be proportional to how well they function, as *Lee and See (2004)* elucidated. When people do not trust technology, they could be hesitant to use it, and when they do trust it too much, they could become dependent on it. According to *Glikson and Woolley (2020)*, elements including AI's openness, dependability, and system behavior determine how much faith people have in the technology. Similarly, when it comes to people's openness to using technology online, trust is crucial (*Gefen et al., 2003*). The risk forecasts and suggestions provided by AI technologies in project management are not always readily verifiable. Project managers must have faith in the precision and dependability of these tools prior to making crucial decisions based on them. These studies highlight the significance of trust in determining the adoption and effective use of AI.

Relationship between Facilitating Conditions, Trust and Adoption

All three—trust, enabling conditions, and AI adoption—are interrelated. According to Venkatesh et al. (2003), technology adoption increases when resources, training, and competent technical support are easily accessible. People are more inclined to use AI when they have faith in it, according to *Glikson and Woolley (2020)* and Lee and See (2004), respectively. Enabling variables that can contribute in trust-building include providing enough training, technological support, high-quality data, and transparent organizational policies. Project managers gain the confidence to utilize AI-powered risk analytics solutions after receiving these amenities. The two main ways in which enabling conditions might affect the adoption of AI are by increasing user confidence and by making technology easier to use. There seems to be a moderating effect of trust between good conditions and the adoption of AI to a certain degree.

Research Gap and Conceptual Framework

The majority of the current research focuses on AI implementations in either healthcare or consumer environments. Project managers rely on predictive risk technologies, yet there is a lack of confidence in these systems and the testing environments they require. This research addresses that need.

The conceptual framework in this paper has the following structure:

- Independent variable: Facilitating Conditions (FC)
- Mediating variable: Trust in AI (TR)
- Dependent variable: Adoption of Predictive AI Risk Tools (AD)

The hypotheses are:

H1: Facilitating conditions have a positive effect on adoption of predictive AI risk tools.

H2: Trust in AI has a positive effect on adoption of predictive AI risk tools.

H3: Facilitating conditions have a positive effect on trust in AI.

H4: Trust in AI partly mediates the effect of facilitating conditions on adoption.

3. Objectives

1. To examine the effect of facilitating conditions on the adoption of predictive AI risk tools in project management.
2. To examine the effect of trust in AI on the adoption of predictive AI risk tools in project management.
3. To test whether trust in AI mediates the relationship between facilitating conditions and adoption.

4. Research Methodology**4.1 Research Design**

A quantitative, explanatory, cross-sectional design was employed in the investigation. Data is collected at a single point in time using a standardized questionnaire, and the hypotheses are tested using statistical tests. The purpose of the study is to quantify the associations between the variables, not to investigate new concepts, hence this design is appropriate.

4.2 Population and Sample

Organizations with access to a predictive AI or analytics solution for project risk are the intended recipients of this message. Project managers, risk managers, PMO members, and team leaders are all part of this target demographic. Members of the IT, construction, finance, and consulting industries made up the sample.

If you want responders with the right kind of experience, you need to utilize a method like purposeful sampling. We intend to poll 220 people. In a two-predictor regression model, the minimum number of cases is typically 100–150; however, Krejcie and Morgan (1970) recommended a larger sample size for large populations.

4.3 Data Collection

Professional networks and email are used to disseminate an online questionnaire that is used to collect data. Anonymity and voluntary participation are maintained. People who take part in the study are made aware of its goals and have the option to stop participating whenever they want.

4.4 Measurement of Variables

All items use a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Prognostic AI risk tools use items reworded from existing scales.

Variable	Code	Items	Source of adaptation	Example item
Facilitating Conditions	FC	5	Venkatesh et al. (2003)	"My organization gives me the training needed to use the AI risk tool."
Trust in AI	TR	5	Mayer et al. (1995); Glikson & Woolley (2020)	"I can rely on the risk predictions given by the AI tool."
Adoption of Predictive AI Risk Tools	AD	4	Venkatesh et al. (2003); Davis (1989)	"I regularly use the AI tool in my project risk reviews."

There were 220 viable responses from the total number of surveys sent out.

4.5 Data Analysis Techniques

Data are analysed in SPSS or an equivalent package in the following steps:

1. Checking for normalcy, outliers, and missing values in the data set.
2. Statistical descriptions of the key factors and responder profiles.
3. Reliability test utilizing Cronbach's alpha, with a minimum acceptable value of 0.70 (Cronbach, 1951; Nunnally, 1978).
4. Use Pearson's correlation to determine the direction and intensity of correlations.
5. Using multiple regression to evaluate hypotheses 1–3.
6. A bootstrap test for the indirect impact to back up the mediation analysis using Baron and Kenny's regression methods.

4.6 Ethical Considerations

Data are analysed in SPSS or an equivalent package in the following steps: The results are given only in aggregate form, and no personal or company identifiers are collected.

4.7 Common Method Bias

Data are analysed in SPSS or an equivalent package in the following steps: In order to mitigate this, we used measures such as making the poll anonymous, using properly stated items, and running the results via Harman's single-factor test.

5. Data Analysis and Interpretation

5.1 Profile of Respondents

There were 220 viable responses from the total number of surveys sent out.

Table 1: Demographic profile of respondents (N = 220)

Characteristic	Category	Frequency	Percent
Gender	Male	128	58.2
	Female	90	40.9
	Other / prefer not to say	2	0.9
Experience	Less than 5 years	54	24.5
	5 to 10 years	91	41.4
	More than 10 years	75	34.1
Role	Project manager	88	40.0
	Risk manager / PMO	52	23.6
	Team leader	47	21.4
	Analyst / other	33	15.0
Industry	IT	82	37.3
	Construction	55	25.0
	Banking	46	20.9
	Consulting	37	16.8

Forty percent of those who took the survey are project managers, and 75.5% have worked in the field for five years or more. Therefore, the sample consists of individuals who have direct experience with project risk and can evaluate AI systems based on their practical use.

5.2 Descriptive Statistics and Reliability

Table 2: Descriptive statistics and reliability

Variable	Items	Mean	Std. Deviation	Skewness	Kurtosis	Cronbach's alpha
Facilitating Conditions (FC)	5	3.62	0.71	-0.31	-0.18	0.84
Trust in AI (TR)	5	3.48	0.78	-0.22	-0.35	0.88
Adoption (AD)	4	3.55	0.74	-0.27	-0.29	0.81

Respondents are leaning toward agreement because all means are over the 3.00 midpoint of the scale. With the lowest mean, trust appears to be the area where people have the least faith in AI results. The data are sufficiently near to normal for regression since skewness and kurtosis are within ± 1 . Because no alpha value is less than 0.70, we can trust these scales. There is no need to be concerned about common method bias because, according to Harman's single-factor test, one factor explains 38.6% of the variation, which is below the 50% limit.

Table 3: Item-level mean scores

Variable	Item focus	Mean
FC	Management support	3.84
FC	Training	3.71
FC	Help desk and technical support	3.60
FC	Integration with project software	3.55
FC	Availability of quality project data	3.40
TR	Accuracy of predictions	3.60
TR	Would rely on tool in decisions	3.58
TR	Reliability over time	3.52
TR	Confidence in tool-based decisions	3.49
TR	Understanding of how predictions are made	3.21
AD	Use in risk reviews	3.62
AD	Use in schedule and cost forecasting	3.59
AD	Intention to continue use	3.51
AD	Use before key decisions	3.48

The availability of data is the weakest prerequisite, whereas support from management is the strongest. The ability to comprehend the prediction process ranks last on the trust scale. The primary areas of concern here are data quality and openness.

5.3 Correlation Analysis

Table 4: Pearson correlation matrix

Variable	1	2	3
1. Facilitating Conditions	1		
2. Trust in AI	0.58**	1	
3. Adoption	0.54**	0.66**	1

** $p < 0.01$ (two-tailed).

There are no negative or insignificant between facilitating conditions and both trust ($r=0.58$) and adoption ($r=0.54$), with trust having the largest correlation with adoption ($r = 0.66$). There is no significant multicollinearity if the correlation coefficient is less than 0.80.associations.

There is a moderate relationship

5.4 Regression Analysis (H1, H2)

Table 5: Multiple regression with Adoption as dependent variable

Predictor	B	Std. Error	Beta	t	p	VIF
Constant	0.58	0.16		3.63	< 0.001	
Facilitating Conditions	0.25	0.063	0.24	3.91	< 0.001	1.51
Trust in AI	0.50	0.057	0.52	8.64	< 0.001	1.51

Model summary: $R = 0.69$, $R^2 = 0.473$, adjusted $R^2 = 0.468$, $F(2, 217) = 97.3$, $p < 0.001$.

The model accounts for 47.3% of the adoption variation. There is significance in both predictions. When compared to facilitating conditions ($Beta = 0.24$), trust has a greater impact ($Beta = 0.52$). Multicollinearity is not an issue because VIF values are far below 5. There is support for H1 and H2.

5.5 Effect of Facilitating Conditions on Trust (H3)

Table 6: Simple regression with Trust as dependent variable

Predictor	B	Std. Error	Beta	t	p
Facilitating Conditions	0.64	0.061	0.58	10.51	< 0.001

Model summary: $R^2 = 0.336$, $F(1, 218) = 110.5$, $p < 0.001$.

33.6% of the variance in trust can be explained by facilitating situations. There is a 0.64-point rise in trust for every one-point increase in conducive conditions. It supports H3.

5.6 Mediation Analysis (H4)

Table 7: Mediation of FC → Trust → Adoption

Path	Effect (B)	Std. Error	p / 95% CI
Total effect: FC → AD (c)	0.56	0.059	$p < 0.001$
FC → TR (a)	0.64	0.061	$p < 0.001$
TR → AD, controlling FC (b)	0.50	0.057	$p < 0.001$
Direct effect: FC → AD (c')	0.25	0.063	$p < 0.001$
Indirect effect: FC → TR → AD (a × b)	0.32	0.047	95% CI [0.22, 0.41]

Because the bootstrap confidence interval (5,000 samples) excludes zero, the indirect effect is significant. The mediation is only partial because the direct effect remains considerable even after trust is added. Trust is responsible for about 56% of the overall impact of adoption-facilitating situations. It supports H4.

5.7 Summary of Hypothesis Testing

Table 8: Hypothesis results

Hypothesis	Statement	Result
H1	FC → Adoption (positive)	Supported
H2	Trust → Adoption (positive)	Supported
H3	FC → Trust (positive)	Supported
H4	Trust partly mediates FC → Adoption	Supported (partial mediation)

6. Findings and Discussion

Even when trust is accounted for in the model, the study indicated that favorable conditions significantly impact the adoption of AI ($B = 0.25$, $p < 0.001$), answering Research Question 1. With a beta coefficient of 0.52, trust in AI was found to be the most significant predictor of adoption. When combined with enabling conditions, trust accounted for 47.3% of the variance in AI adoption, answering Research Question 2. Additionally, the results showed that trust is moderately influenced by facilitating conditions and that trust in turn influences the association between facilitating conditions and AI adoption ($Beta = 0.58$). In answering Research Question 3, trust accounted for about 56% of the overall impact. The study did find two big areas that could use some work, though: (1) the accessibility of high-quality data (Mean = 3.40) and (2) the clarity of AI forecasts (Mean = 3.21). The results show that trust, organizational backing, high-quality data, and openness are key factors in getting people to use AI.

Discussion

Research by Venkatesh et al. (2003) and others has shown that enabling conditions are crucial to the acceptance and usage of technology. The study's results are in line with this theory. Accurate and up-to-date data, technical assistance, and interaction with preexisting project management systems are essential for AI-based risk analytics tools in project management. In their absence, project managers may revert to tried-and-true techniques like risk registers and spreadsheets. The study's findings on the importance of trust in AI adoption lend credence to the claims made by *Lee and See (2004)*, who argued that users place greater reliance on automated processes when they see them as trustworthy. Trusting the accuracy and reliability of AI-based risk forecasts is essential for project managers, as they cannot usually be checked instantly. This result is in line with what *Glikson and Woolley (2020)* found, which is that trust in AI can only be built through being trustworthy and open. In addition, trust's partly mediating role suggests that enabling factors impact adoption in two ways: directly and indirectly. Improving trust and encouraging AI adoption can be achieved through proper training, quality data, technological assistance, and clear organizational policies. Improving technology and managing change effectively are two aspects of project management that are necessary for applying AI risk analytics. Decisions made by project managers are ultimately accountable to stakeholders, and those managers must be competent to explain the reasoning behind AI-generated suggestions. Hence, the results further demonstrate that project management is most effective when stakeholders are actively involved, kept informed, and held accountable (*PMI, 2021*).

7. Limitations

1. Since data is only available at a single moment in time, the study can only demonstrate associations, not causes. There may be a reciprocal effect between trust and adoption.
2. People may exaggerate or underestimate the amount of AI tools they employ. While we did our best to eliminate common method bias, it remains. It is difficult to extrapolate the findings to other industries or nations due to the use of purposive sampling and the inclusion of only four industries.
3. We only look at two potential predictors. The exclusion of factors including social impact, perceived risk, performance anticipation, and effort expectancy leaves 53% of the adoption variation unaccounted for.
4. People's perceptions of trust may vary depending on their familiarity with artificial intelligence.

8. Recommendations

1. Enhance the quality of project data and incorporate AI techniques into current software.
2. Assign explicit decision-making responsibilities, technical assistance, and hands-on training.
3. To assess AI predictions and foster confidence, carry out trial initiatives.
4. AI can help with human judgment and efficient project management.
5. Provide visible AI technologies that are easy to integrate, provide explicit forecasts, and have varying degrees of accuracy.
6. Future research should use PLS-SEM across several industries, longitudinal investigations, and additional adoption variables.

9. Conclusion

From a project management perspective, this study looked at how trust and favorable conditions impact the application of predictive AI risk solutions. Both traits have a positive and significant impact on adoption, according to the study, but trust has a greater impact and helps to explain how adoption is made easier. It is a useful message. Investing in predictive AI technologies is insufficient. Organizations must also provide the data, integration, training, and management support for the technology to be viable. They also need to build credibility by

being transparent about their predictions and proving their correctness over time. When combined, these two elements raise the possibility that project teams will use AI in routine risk management, and projects are better equipped to recognize and handle risks before they become problems. Because of its design and sample limitations, the study's findings need be confirmed by additional research. Nonetheless, the model gives scholars and professionals a solid basis for understanding why certain project teams use predictive AI while others do not.

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