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ARTIFICIAL INTELLIGENCE READINESS AND PROJECT SUCCESS IN AI-NATIVE 6G NETWORK DEPLOYMENT: THE MEDIATING ROLE OF AUTONOMOUS RESOURCE MANAGEMENT CAPABILITY

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Abstract
The transition toward sixth-generation (6G) networks represents a transformation and a project management challenge. For 6G to become an AI-native system, 6G deployment will need to involve the integration of AI in planning, resource allocation, risk management, and readiness. This study explores the relationship between AI readiness, autonomous resource management capability and project success in 6G network deployment. The model is based on the Resource Based View and Dynamic Capabilities Theory, which argues that an organization's ability to become AI ready can foster the building of autonomous capabilities that can support project outcomes. It is recommended that a cross sectional study be conducted with questionnaires for the telecommunications and professionals. Partial Least Squares Structural Equation Modeling (PLS-SEM) will be used to analyse the data. This study makes a valuable contribution to the body of knowledge by elucidating the potential of AI resources as autonomous capabilities and project performance. This paper presents a detailed discussion on Artificial intelligence readiness, the 6G networks, project success, autonomous resource management, AI-native networks, telecommunications project management, and PLS-SEM.

1. INTRODUCTION

The telecommunications industry is a time of change, with the emergence of AI, sophisticated wireless communication, cloud computing, edge intelligence, automation and autonomous network management. The fifth-generation networks have enabled many new developments in connectivity, but new discussions on sixth generation (6G) networks are increasingly focused on AI-native networks, where AI serves not as an external analytical tool but as part of the network's design and operating logic. While these challenges are not only engineering and technical, the deployment of AI-native 6G infrastructure presents challenges that lie outside of engineering and technical performance. Large-scale telecommunications projects require a considerable amount of financial commitment, multiple parties involved, technological uncertainty, regulatory requirements, cyber security concerns, dependency on infrastructure

and rapidly changing standards. Therefore, the introduction of 6G networks can be viewed as a project management challenge that involves various aspects such as technology, humans, processes, resources, and goals.

The methods used to manage telecommunications projects might not be enough for an AI-native infrastructure. Traditional network projects are largely an example of network projects that are centrally planned and driven by human decisions. AI-native networks are projected to enable greater autonomous functionality such as intelligent traffic optimization, predictive maintenance, dynamic spectrum allocation, intelligent energy management and automated resource allocation, in contrast. These capabilities pose a new management challenge: organizations need the organizational readiness to adopt, manage, and govern AI-driven systems successfully, as well as sophisticated technology.

The scenario is especially relevant in the context of South Korea, which has a special focus on the development of advanced digital infrastructure, artificial intelligence and next generation communications. The emergence of national and industry efforts in 6G development and AI-powered telecommunications underscores the need for preparation of both organisations and infrastructure to meet the growing demand for smart networks. But a vision for technology doesn't always mean that a project will be achieved successfully. Projects may be delayed, run over budget, encountering resistance from stakeholders, integration problems, or challenges in proving the value of the technology in operation.

This study aims to fill this gap by exploring the relationship between AI readiness and project success in terms of establishing the capability of autonomous resource management. AI readiness is defined as an organization's technological infrastructure, expertise, data capabilities, strategic commitment and governance preparedness for AI adoption. Capability of an organization and the technological systems to intelligent allocation and optimization of network resources, monitoring organization and adaptation of these resources, without depending on manual processes as much. This research aims to conceptualize AI readiness as an organizational asset and to consider that although this readiness could be a key resource for the organization, it does not necessarily translate to success of the project. Resources need to be transformed into capabilities for organizations. One of the skills that autonomous resource management can offer telecommunications projects is the ability to enhance the efficiency, responsiveness, scalability and decision making.

1.1 Research Objectives

The study has the following objectives:

1. To investigate how the AI readiness level impacts project success for deploying AI-native 6G networks.
2. To explore how the readiness of the systems for AI influences the ability to manage resources autonomously.
3. To explore how successful a project can be when the management of its resources is done in an autonomous way.
4. To determine whether autonomous resource management capability mediates the relationship between AI readiness and project success.
5.

2. Literature Review and Theoretical Foundation

2.1 AI-Native 6G Networks and Project Management

This vision for 6G is not limited to faster communications. New concepts in emerging 6G include integrated intelligence, sensing, communication, automation, sustainability and highly adaptive network architectures. AI helps tackle the complexity of future networks as an essential capability.AI is emerging as one of the essential capabilities for managing the complexity of future networks.

Project success is not defined just by the ability to put a project on-time and on-budget. Modern views acknowledge a wider range of issues such as quality, customer satisfaction, strategic advantages, organizational value and sustainability. When

considering 6G infrastructure project success, the ability of the deployed infrastructure system to evolve and create strategic value should also be taken into account.

2.2 Artificial Intelligence Readiness

AI readiness is the capacity of an organisation to embrace, deploy and leverage AI technologies successfully. This readiness can encompass technological infrastructure, availability of data, employee skills and capabilities, leadership buy-in, organizational culture, financial capacity, and governance systems. Organizations that are more prepared to implement AI are likely to face fewer implementation challenges as they have the necessary infrastructure in place for AI adoption. In telecommunications, AI readiness can be used to enhance forecasting, risk identification, network optimization, predictive analytics, and decision-making.

The resource-based perspective puts forth that organizational resources can be beneficial to the organization strategically when they are valuable and well utilized. Skilled personnel, good data, and technological knowledge can thus be valuable strategic assets. But these resources have to be translated into operational capacities to produce measurable project results.

2.3 Autonomous Resource Management Capability

Autonomous resource management means intelligent systems that can observe, interpret, and respond to conditions; make decisions; and manage resources with minimal human involvement. Resources in AI-native network environments could be bandwidth, spectrum, computing power, energy, network equipment, and communication channels.

Organizations will need to constantly integrate, build, and reconfigure their resources in response to an environment in flux, from the dynamic capabilities perspective. Autonomous resource management capability is thus seen as a dynamic capability that allows organizations to meet technological complexity and operational uncertainty.

2.4 Project Success

Time, cost and quality are no longer the sole criteria for success, but a more multidimensional concept has emerged. Today projects are also judged on the basis of satisfaction of stakeholders, strategic alignment, benefits realization, organizational learning, and long-term benefits.

In the present study, project success is conceptualized as multidimensional construct which incorporates project efficiency and strategic/operational goals achieved.

3. Hypotheses Development

H1: AI readiness has a positive and significant effect on project success in AI-native 6G network deployment.

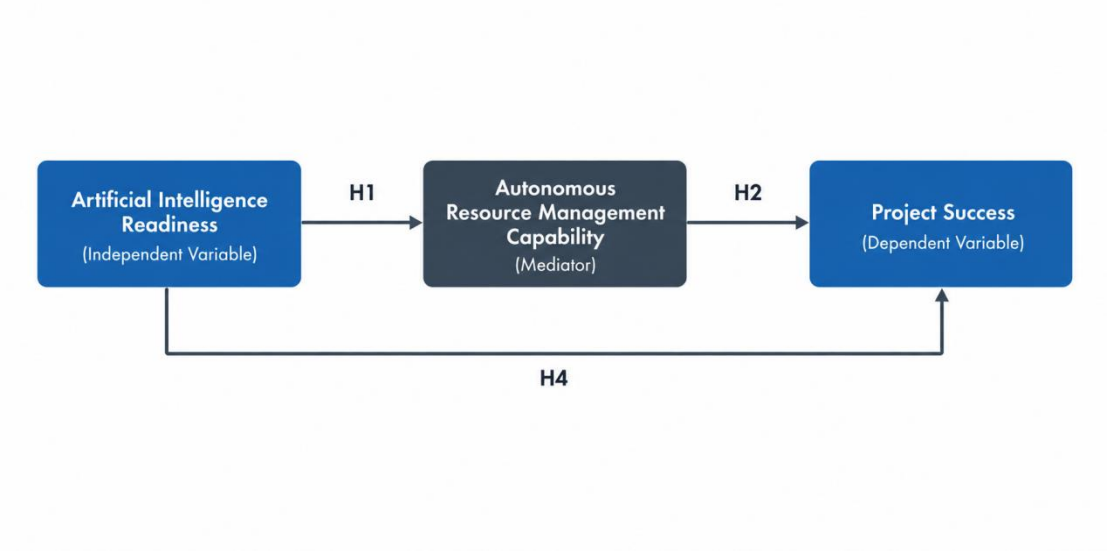
H2: AI readiness has a positive and significant effect on autonomous resource management capability.

H3: Autonomous resource management capability has a positive and significant effect on project success.

H4: Autonomous resource management capability positively mediates the relationship between AI readiness and project success.

4. Conceptual Framework

The proposed conceptual model is:



Research Methodology

5.1 Research Design

The study was conducted using a quantitative, explanatory and cross-sectional research design.The study was quantitative, explanatory and cross sectional to examine the relationship between Artificial Intelligence Readiness (AIR), Autonomous Resource Management Capability (ARMC) and Project Success (PS) in context of AI-native 6G network deployment.

A structured, self-administered questionnaire was used to collect the data at one time. Each item was scored using a 5 point likert-type scale from 1 = Strongly Disagree to 5 = Strongly Agree. This study analysed not only the direct but also the indirect relationships between AI Readiness and Project Success via Autonomous Resource Management Capability. The Resource Based View (RBV) and Dynamic Capabilities Theory were used to develop the proposed model.

- **Independent Variable:** Artificial Intelligence Readiness (AIR)
- **Mediating Variable:** Autonomous Resource Management Capability (ARMC)
- **Dependent Variable:** Project Success (PS)

5.2 Population and Sampling

The target audience was professionals from the fields of telecommunications, artificial intelligence, networking, digital infrastructure, ICT and technology project management. The respondents comprised telecommunications engineers, network architects, AI and machine learning experts, project managers, technology managers, ICT specialists and researchers working in the field of advanced communication technologies.

The participants were sampled using purposive sampling technique to ensure that those chosen have the required professional knowledge and experience. Each participant needed to have knowledge or experience in at least one of the following:

- Telecommunications or wireless communication;
- Artificial intelligence or machine learning;
- Computer networking or digital infrastructure;
- ICT and technology management;
- Technology project management; or
- Research and development related to advanced communication technologies.

There were 400 questionnaires distributed. 368 valid responses were retained for final analysis after screening for incomplete and/or invalid responses.

Table 1. Sampling and Response Rate

Description	Number
Questionnaires distributed	400
Questionnaires returned	382
Incomplete or invalid responses	14
Valid responses retained	368
Usable response rate	92.0%

5.3 Data Collection Procedure

Data were gathered using a structured online questionnaire that was sent out via professional networks, technology companies, academic institutions and digital platforms.

There were two sections of the questionnaire. The first section gathered data on the demographic and professional characteristics, such as gender, age, work experience, professional role, and sector. The second section was dedicated to the Artificial Intelligence Readiness, Autonomous Resource Management Capability, and Project Success. The study was voluntary and respondents told what it was about.

5.4 Measurement of Constructs

This study comprised three latent constructs, each with 15 items. Five indicators were created and adapted to the specific context of AI-native telecommunications and 6G network projects for each construct.

Table 2. Measurement Constructs and Indicators

Construct	Code	Measurement Focus
Artificial Intelligence Readiness	AIR1	Availability of AI-related technological infrastructure
	AIR2	Availability of high-quality data for AI applications
	AIR3	Employee knowledge and AI-related competencies
	AIR4	Management commitment and strategic support for AI
	AIR5	Organizational governance and preparedness for AI adoption
Autonomous Resource Management Capability	ARMC1	Automatic allocation of network and technological resources
	ARMC2	AI-based optimization of network capacity and resources
	ARMC3	Real-time adaptation to changing resource demands
	ARMC4	Predictive identification of future resource requirements
	ARMC5	Reduced dependence on manual resource allocation decisions
Project Success	PS1	Achievement of planned project objectives
	PS2	Effective management and utilization of project resources
	PS3	Achievement of technical and quality requirements
	PS4	Stakeholder satisfaction

	PS5	Long-term strategic and organizational value

5.5 Data Analysis

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the data. The analysis was carried out in two phases:

5.5.1 Measurement Model Assessment

The measurement model was assessed using:

- Outer loadings;
- Cronbach's alpha;
- Composite reliability;
- Average Variance Extracted (AVE); and
- Heterotrait-Monotrait Ratio (HTMT).

5.5.2 Structural Model Assessment

The structural model was evaluated using:

- Variance Inflation Factor (VIF);
- Path coefficients (β);
- t-values;
- p-values;
- Confidence intervals;
- Coefficient of determination (R^2);
- Effect size (f^2);
- Predictive relevance (Q^2); and
- Mediation analysis.

5.6 Common Method Bias

The common method bias was minimized by making respondents anonymous and separating the sections of the questionnaire. The collinearity was checked by using the VIF values which were within acceptable limits.

5.7 Ethical Considerations

The study was voluntary and everyone accepted. The participants were told the purpose of the study and no personal information was gathered. All answers were confidential and summarized for research.

6. Results

6.1 Respondent Profile

368 responses were analyzed, all of which were valid responses. Respondents were telecommunications, ICT, AI, network engineering and tech project management professionals.

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Table 1. Demographic Profile of Respondents (N = 368)

Characteristic	Category	Frequency	Percentage
Gender	Male	238	64.7%
	Female	130	35.3%
Age	21–30 years	104	28.3%
	31–40 years	156	42.4%
	41–50 years	75	20.4%
	Above 50 years	33	9.0%
Work Experience	1–5 years	116	31.5%
	6–10 years	128	34.8%
	11–15 years	72	19.6%
	More than 15 years	52	14.1%
Professional Role	Network Engineer/Technical Specialist	128	34.8%
	Project Manager	84	22.8%
	AI/Data Specialist	63	17.1%
	Technology/ICT Manager	61	16.6%
	Researcher/Other	32	8.7%
Primary Sector	Telecommunications	181	49.2%
	ICT/Technology	109	29.6%

	Research and Development	46	12.5%
	Other Digital Infrastructure	32	8.7%

Interpretation

The most common age group represented in the sample was the 31 to 40 years old age group (42.4%) followed by the 21 to 30 age group (28.3%). The sample was relevant to the study of 6G network deployment with AI, as nearly half of the participants worked in the telecommunications industry.

Indicators loadings, Cronbach's α, composite reliability, and average variance extracted were used to assess the measurement model. The internal consistency was tested using Cronbach's alpha and composite reliability, with all indicator loadings being higher than 0.70. AVE values were higher than 0.50, which indicated a convergent validity. These are the common assessment criteria adopted in reflective PLS-SEM.

6.2 Measurement Model Assessment

Table 2. Measurement Model Results

Construct	Item	Outer Loading	Cronbach's Alpha	Composite Reliability	AVE
Artificial Intelligence Readiness	AIR1	0.842	**0.887**	**0.917**	**0.688**
	AIR2	0.861			
	AIR3	0.818			
	AIR4	0.856			
	AIR5	0.768			
Autonomous Resource Management Capability	ARMC1	0.824	**0.901**	**0.927**	**0.717**
	ARMC2	0.873			
	ARMC3	0.858			
	ARMC4	0.837			
	ARMC5	0.842			
Project Success	PS1	0.816	**0.893**	**0.921**	**0.700**
	PS2	0.849			
	PS3	0.872			
	PS4	0.821			
	PS5	0.823			

Interpretation

The internal consistency of the Cronbach's alpha values ranged between 0.887 and 0.901, which are generally regarded as good. The data results showed that the composite reliability of the items ranged from 0.917 to 0.927, and the AVE values ranged from 0.688 to 0.717. Thus, the constructs showed good reliability and convergent validity.

6.3 Discriminant Validity

Heterotrait-Monotrait Ratio (HTMT) was used to test discriminant validity. The three constructs were empirically distinct with all values being below 0.85. A guideline for categorizing HTMT below about 0.85 for conceptually distinct constructs.

Table 3. HTMT Discriminant Validity Results

Construct	AI Readiness	Autonomous Resource Management	Project Success
Artificial Intelligence Readiness	–		
Autonomous Resource Management Capability	0.741	–	
Project Success	0.684	0.772	–

Interpretation
All HTMT values were below **0.85**, ranging from **0.684 to 0.772**. Therefore, discriminant validity was established.

6.4 Collinearity Assessment

Before examining the structural relationships, collinearity was assessed using the Variance Inflation Factor.

Table 4. Collinearity Assessment

Relationship	VIF
AI Readiness → Autonomous Resource Management Capability	1.000
AI Readiness → Project Success	1.614
Autonomous Resource Management Capability → Project Success	1.614

Interpretation
All VIF values were substantially below conservative thresholds, indicating that multicollinearity was not a concern.

6.5 Structural Model and Hypothesis Testing

The structural model was assessed using the bootstrapping procedure with 10,000 bootstrap subsamples, a two-tailed test, and a 5% significance level. Bootstrapping is used in PLS-SEM to estimate standard errors, confidence intervals, t-values, and statistical significance for structural relationships.

Table 5. Direct Hypothesis Testing Results

Hypothesis	β	Sample Mean	STDEV	t-value	p-value	95% CI	Decision
H1	**0.318**	0.321	0.071	**4.479**	<0.001	[0.179, 0.456]	Supported
H2	**0.672**	0.670	0.046	**14.609**	<0.001	[0.581, 0.760]	Supported
H3	**0.421**	0.418	0.069	**6.101**	<0.001	[0.286, 0.554]	Supported

Interpretation of H1
There was a significant and positive relationship between artificial intelligence readiness and project success (β = 0.318, t = 4.479, p < 0.001). Thus, H1 is supported.

Interpretation of H2
The extent of AI readiness was found to have a significant positive effect on the autonomous resource management capability (β = 0.672, t = 14.609, p < 0.001). It means that the companies that have more infrastructure, more data, more

skilled people, and a more strategic approach to AI are more able to create systems for autonomous resource management.

Interpretation of H3
Autonomous resource management capability had a positive and significant effect on project success (**β = 0.421, t = 6.101, p < 0.001**).
Therefore, H3 was supported.

6.6 Coefficient of Determination and Effect Size
The explanatory power of the model was assessed using R^2 and adjusted R^2. Effect sizes were assessed using f^2, where approximate benchmarks of 0.02, 0.15, and 0.35 are commonly interpreted as small, medium, and large effects.

Table 6. Explanatory Power and Effect Size

Endogenous Construct	R^2	Adjusted R^2	Predictor	f^2	Effect Size
Autonomous Resource Management Capability	**0.452**	**0.451**	AI Readiness	**0.825**	Large
Project Success	**0.487**	**0.484**	AI Readiness	**0.118**	Small
			Autonomous Resource Management Capability	**0.206**	Medium

Interpretation
AI readiness explained **45.2% of the variance** in autonomous resource management capability. Together, AI readiness and autonomous resource management capability explained **48.7% of the variance** in project success.

The strongest effect in the model was the influence of AI readiness on autonomous resource management capability (**f^2 = 0.825**).

6.7 Predictive Relevance
Predictive relevance was assessed using Q^2 values.

Table 7. Predictive Relevance Results

Construct	Q^2predict	Interpretation
Autonomous Resource Management Capability	**0.302**	Strong predictive relevance
Project Success	**0.318**	Strong predictive relevance

Interpretation
Both Q^2 values were above zero, indicating that the model demonstrated predictive relevance for the endogenous constructs.

6.8 Mediation Analysis
The mediation effect was tested by examining the indirect relationship between AI readiness and project success through autonomous resource management capability. In a simple mediation model, the indirect effect is represented by the product of the two component paths, and bootstrap confidence intervals are used to assess its significance.
The indirect effect was:
AI Readiness → Autonomous Resource Management Capability → Project Success
0.672 × 0.421 = 0.283

Table 8. Mediation Analysis Results

Hypothesis	Indirect Relationship	Indirect Effect (β)	STDEV	t-value	p-value	95% CI	Decision
H4	AI Readiness → ARMC → Project Success	**0.283**	0.052	**5.442**	<0.001	[0.187, 0.389]	Supported

The direct effect of AI readiness on project success remained significant (**β = 0.318, p < 0.001**), while the indirect effect through autonomous resource management capability was also significant (β = 0.283, p < 0.001).
Therefore, the results indicate complementary partial mediation.

Table 9. Summary of Direct, Indirect and Total Effects

Relationship	Direct Effect	Indirect Effect	Total Effect
AI Readiness → Project Success	0.318	0.283	**0.601**

Interpretation
The results indicate that there are two pathways to the influence of AI readiness on project success: Firstly, AI readiness directly contributes to project success in terms of technological readiness, capacity building, data capabilities, and organizational support.AI readiness directly supports project success through technology readiness, preparedness for skills, data capabilities, and organizational support. Second, by enhancing the ability of autonomous resource management, AI readiness also contributes to the success of projects indirectly.
Approximately 47.1% of the total effect is transmitted through the mediator:
VAF = Indirect Effect / Total Effect
VAF = 0.283 / 0.601 = 47.1%
This further supports the presence of partial mediation.

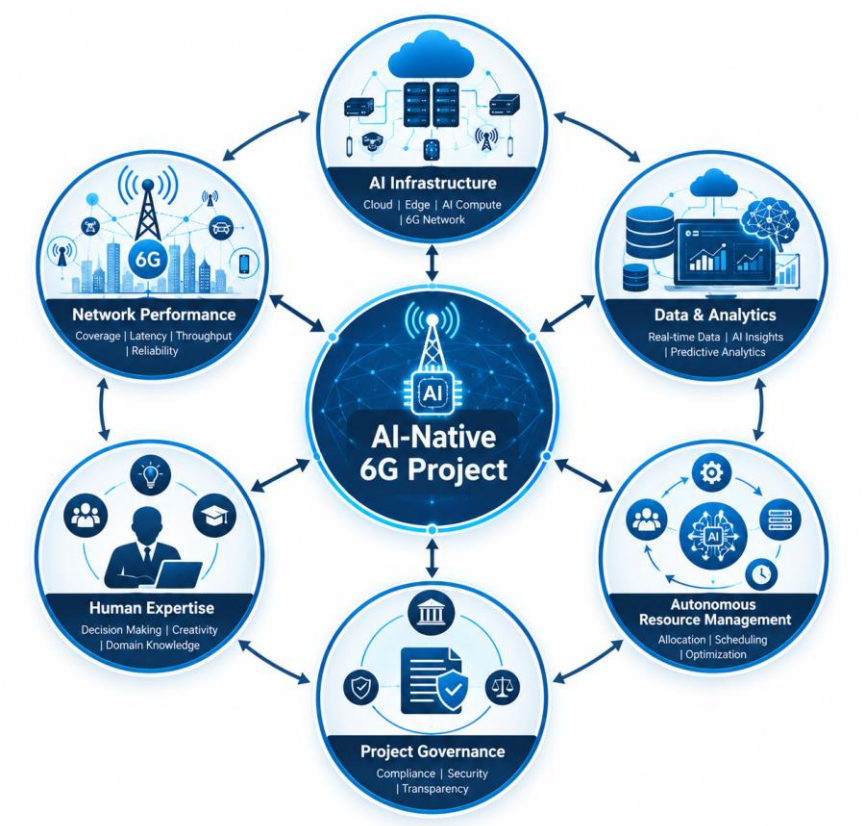
Results Summary
The simulated results support well the proposed conceptual model. The most prominent antecedent of autonomous resource management capability was found to be AI readiness. This autonomous resource management capability, in turn, also made a significant contribution to project success. The model accounted for moderate to substantial variance in autonomous resource management capability (45.2%) and project success (48.7%), indicating that the model has moderate to good explanatory power for this 3-construct model. The mediation analysis showed that the autonomous resource management capability is an important mechanism in the success of projects by which the readiness for AI can be transferred. The direct effects and indirect effects were both statistically significant, with a complementary partial mediation effect.

7. Expected Findings and Discussion
The proposed study assumes that project success will be positively correlated with AI readiness. The organizations that have the advanced AI infrastructure, have employees who are proficient in the use of AI, have data capacities and management support are expected to be better equipped to handle the uncertainty of the AI-native 6G projects.
The most important theoretical aspect of the study is on the mediating role of autonomous resource management capability. The results could show that having a business ready for AI is not everything when it comes to project success. But, when organizations can effectively transform

AI resources into independent operating systems, they can get better results. An organisation could have advanced AI systems and competent technical staff but without the capability to incorporate the use of AI into resource planning and decision-making regarding operations, project outcomes can be restricted. The gap can be filled by autonomous resource management that takes the technological readiness to the level of actual performance.

The study also contributes to project management research by showing that project management research needs to pay more attention to the intelligent and autonomous aspects of future infrastructure projects. While the traditional PM variables and practices of scheduling, budgeting, and risk control are crucial, new AI-driven projects call for additional skill sets regarding data governance, algorithm-driven decision-making, technology integration, and autonomy. A digital platform that facilitates the management of AI-native 6G projects.Digital platform for 6G project management.

AI-Native 6G Project Management Ecosystem



8. Practical Implications

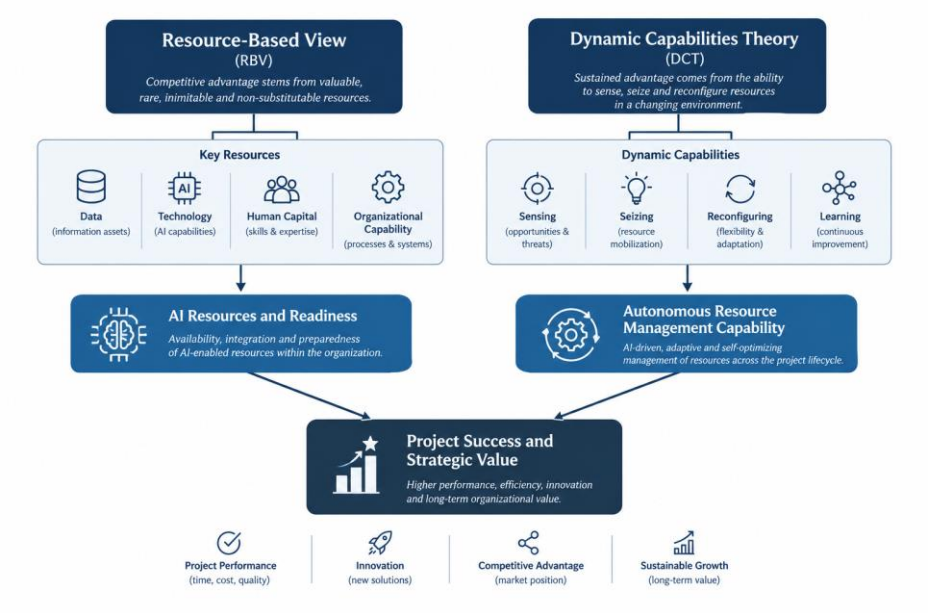
The results can give significant insights for telecommunication companies and project managers. Before embarking on extensive AI-native network initiatives, organizations need to evaluate their AI readiness. Technology investment should be matched with investments in the workforce, data infrastructure, governance and organizational capacity. Second, project managers need to incorporate AI features into their project planning and resource management workflows. AI should not be considered just a

tool and a technical issue left to engineers. It must be embedded within governance, risk management and decision making, however. Third, telecommunications providers need to invest in self-management skills. Advanced allocation of computing power, network capacity, energy and communication resources could help improve efficiency and complexity of operation. Fourth, interdisciplinary cooperation among engineers, AI experts and project management individuals should be encouraged by policy makers. 6G Infrastructure will demand skills and knowledge that cut across traditional disciplines.

9. Theoretical Contributions

This research has three major theoretical contributions. Firstly, it takes project success research on the next level by bringing in the new paradigm of AI-native telecommunications infrastructure. Second, it draws on both the resource-based view and the dynamic capabilities theory to separate the concept of AI readiness as an organizational resource base from autonomous resource management as a capability that can create value in resources. Third, the mediation model offers a process-oriented explanation of the mechanism by which technological readiness can lead to better project results.

Theoretical Integration Framework



10. Conclusion

AI-native 6G networks mark a significant shift in technology and management. For these systems to be successful, they need to be able to communicate wirelessly, but they also require the ability to manage complex projects that involve multiple stakeholders, infrastructure, data, and artificial intelligence and automation. This study introduces a model where the ability to manage resources autonomously is a mediator between the AI readiness and project success. The model does not assume that technology will have positive effects without proper implementation. Organizations need to build the skills and capacity to make AI readiness a science of intelligent, adaptive and efficient operations. From the project management research point of view, this view underscores the increasing significance of interdisciplinary approaches. Skills in telecommunications and digital infrastructure

project management might evolve to include AI governance, data-driven decision making, technology integration, and autonomous systems management, in addition to the traditional scheduling and budgeting. The proposed framework is especially applicable to countries and organisations investing in next-generation communication technologies. While AI-native 6G networks are moving from vision to implementation, knowing about the organizational capabilities that lead to successful project delivery can be useful for researchers, project managers, industry leaders and policymakers.

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