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How Organizations Legitimize AI Led Organizational Change?

Gyeung-min Kim[a,*], Heesun Kim[b]

[a] *Professor, College of Business, Ewha Womans University, Korea*
[b] *Professional, Hyundai Autoever IT Service Innovation Team, Korea*

A B S T R A C T

AI is recognized to be a key technology for digital transformation (DT) and the value of AI is considered to determine the future of the company. However, in reality, although managers acknowledge the future value of AI and have plans to introduce it, most are not sure what to expect from AI or how to apply it to their business. This study compares two company cases to demonstrate how an organization has successfully achieved AI led organizational change while another failed. Specifically, by taking institutionalist's view, this study examines how the legitimacy enables and constrains AI led organizational changes in organization's practices, processes, and infrastructure. The results of this study indicate that for the success of AI led organizational changes, the legitimacy plays an important role by reducing the challenges from stakeholders and increasing the institutional momentum to move through the phases of the change.

Keywords: AI, Legitimacy, Digital Transformation, Institution, Data Governance

Ⅰ. Introduction

The discourse that artificial intelligence (AI) is an enabler for digital transformation (DT in short hereinafter), is spreading regardless of industry sector. While this discourse is spreading, in reality most managers are not sure how to apply AI to their business (Ransbotham et al., 2017). Often, investments made in AI result in short-term pilot projects and fail to advance to DT (Davenport and Ronanki, 2018). Achieving DT by investing in AI means that the results learned from the data and the model are applied to improve customer experiences, achieve process innovation, and create new business (Gartner, 2021). Advancing to DT requires not only collaboration between IT and business process owners, but also investment in new digital infrastructure followed by changes in business processes and organizational competency.

In practice, IT-led organizational changes, such

*Corresponding Author. E-mail: gkim@ewha.ac.kr

as process innovation (PI) with an ERP (Enterprise Resource Planning) system, have demonstrated that obtaining legitimacy for the investments in new infrastructure and associated process reengineering are pre-requisites for the PI success. Since AI-led DT is recognized as a major force in replacing human workers with machines (Ransbotham et al., 2017), it is important to obtain and establish the legitimacy for AI-led DT to ensure the DT success.

Institutions are a system of symbols (e.g., laws, values, and expectations), relations (e.g., governance mechanisms and authority structures), routines (e.g., procedures and protocols) and artifacts (e.g., standards and conventions) (Scott, 2001). Legitimacy as a condition reflecting perceived agreement with the institutional framework plays an important role in the institutional theory to rationalize a firm's strategic choices and resource allocations (Deephouse et al., 2017; Scott, 2001). In earlier studies of the institutional theory, isomorphism, referring to a firm's conformance to industry recopies, received great attention as ways to minimize legitimacy challenges in relation to its strategic choices (Dimaggio and Powell, 1983). Later, institutionalists take a more strategic view that legitimacy is a resource (Ashforth and Gibbs, 1990). Thus, more management control and manipulation over the process of legitimation is necessary to achieve the organization's goal.

In the IS domain, institutional theory has received great attention to study how the institutional context enables and constrains social actors (managers, developers, users etc.) in IS adoption and use (Lamb and Kling, 2003; Volkoff and Strong, 2013). By taking the theoretical stance that the success of AI led transformation can only be understood by considering both technology and the institutional context, this study aims to examine how organizations legitimize AI-led DT. Specifically, this study examines how organizations successfully achieved AI-led DT by legitimizing required resource allocation and delegitimizing the stabilized existing organizational arrangements such as practices, processes, and infrastructure in order to adopt new practices, processes, and systems during the journey of DT. In the subsequent sections, the literature on AI and legitimacy are reviewed. Then, research methodology, data analysis and research findings are presented. Finally, discussions and future research are proposed.

Ⅱ. Literature Review

2.1. AI as a Game Changer

AI systems are different from traditional systems in that they revolve around data. AI systems require not only input datasets to generate the model for prediction but also test datasets to validate the model. Further, the model's performance is improved with real-world data as it operates. Since the performance of AI systems improves with the amount of data, the organization's biggest challenge in deploying AI systems is collecting and preparing data for training and testing (Daugherty and Wilson, 2018).

AI is considered to be a game changer and deliver dramatically enhanced or new value propositions to customers (Ross et al., 2017). For this reason, leading firms approach AI to reshape their business strategies and transform their capabilities to ultimately create new value in the market. The strategic approach examines business strategies and goals that might be advanced through AI. To support the strategic approach, establishing data supply chains is key (Ransbotham et al., 2017). The data may be supplied by persuading data owners (Def., a senior-level employee accountable for the quality of one or more datasets) to share the data if the data owners are within the organization, and through data consolidation if the data are fragmented across data sources. Data can be bought from the market or contracted for data supply. However, when it is not possible to obtain data due to market competition, investment in data is necessary to bring new sources to the data platform. One such example is implementing digital strategies to fuel real-time data through the use of digital technologies such as IoT (Porter and Heppelmann, 2014; Porter and Heppelmann, 2015; Sebastian et al., 2017).

Criticality of a firm's predictive analytics capabilities on business performance has been iterated by many scholars. In a study on the effects of analytical capabilities and cloud-based ERP data on a firm's performance, big data predictive analytics (BDPA) capabilities composed of data, management skills, and technical skills have a positive impact on a firm's market and operational performances (Gupta et al., 2019). Data dimension is comprised of the ability to access a very large amount of internal and external data. Management dimensions consist of the abilities of analytics managers to be able to work with stakeholders and to be able to understand how to apply big data to the business. The technical dimension is composed of the availability of big data analytics staffs with experiences.

Mikalef et al. (2019) adds an intangible dimension to the big data analytics capability: data-driven culture and organizational learning. Tarafdar et al. (2019) believes that for cognitive computing, business should possess capabilities in data science, operational backbone, and digital technologies.

2.2. Institutionalist View of Legitimacy

Prevailing views of institutions are a system with three pillars--normative, cultural-cognitive and regulatory--that become the basis of legitimacy. An institution's normative pillar includes values and norms. "Values are conception of the preferred or the desirable, together with the construction of standards to which existing structures or behaviors can be compared and assessed. Norms specify how things should be done; they define legitimate means to pursue valued ends. Normative systems define goals but also designate appropriate ways to pursue them (Scott, 2001, pp. 54-55)." In an organizational context, some norms and values are applicable only to selected actors. By defining positions, the selected actors are assigned with roles and responsibilities. That is, the social actors are given the goals and activities. The appropriate goals and activities assigned to the actors become normative expectations that not only constrain but also empower to perform social behavior. Thus, the normative pillar introduces prescriptive, evaluative, and obligatory dimensions to social life (Scott, 2001).

Normative (or moral) legitimacy reflects an evaluator's point of view based on socially constructed value systems rather than a constituents' self-interest. The earlier studies on normative aspects of the institutions are mostly done by sociologists, and they tend to focus on moral values and beliefs of religious groups or social welfare. In an organizational context, *normative pressure* stem from professional norms (Dimaggio and Powell, 1983). The examples for organizational context include when the evaluator judges whether a given practice being evaluated is the right thing to do from the evaluator's point of view. Normative legitimacy is further defined as consequential, procedural, structural, and personal legitimacy. While *consequential legitimacy* relies on socially accepted outputs and consequences, *procedural and structural legitimacies* rest on socially accepted procedures and structure respectively. *Personal legitimacy* is based on the evaluation of an organization's leaders and representatives.

The cultural-cognitive pillar of institution is defined as "the shared conceptions that constitute the nature of social reality and the frames through which meaning is made…a collection of internalized symbolic representations of the world mediating between external world of stimuli and the response of the individual organism" (Scott, 2001, p. 57). Cognitive means collective programming of the human mind and un-spoken assumption (Hofstede, 1980). Cultural-cognitive legitimacy is based on cognition and a cultural model that explains organizations and its endeavors. Cultural-cognitive legitimacy represents mere acceptance without questions (Leigh, 2011). The cultural-cognitive legitimacy is legitimacy based on being taken-for-granted (Suchman, 1995).

The regulatory pillar is different from the others by having regulatory processes: rule-setting, monitoring, and sanctioning (Scott, 2001). These processes could be informalized or highly formalized such as laws, policies, and directives. Regulatory legitimacy is based on internal and external regulatory mandates by government and executive managers; implicit and explicit executive manager's directives are the regulatory pillar of institutions. While fear is a central theme of the regulatory pillar, inducement can also be used to secure compliance. ***Coercion,*** political power either formal or informal, is an important way to control the behavior of organizations or individuals to conform to the rules (Dimaggio and Powell, 1983). Authority is used as a way to legitimize the coercive power. Thus, "coercive power is legitimated by a normative framework that both supports and constrains the exercise of power (Scott, 2001, p. 53)." In sum, regulatory and normative elements of the institutions are re-enforcing.

In addition to the three types of legitimacy described above, pragmatic legitimacy is defined by Suchman (1995). Self-interested calculations of an entity's immediate constituencies become the basis of the ppragmatic legitimacy. The constituency supports the entity because its presence produces higher value than its absence. Pragmatic legitimacy includes exchange, influence and dispositional legitimacies. The *exchange legitimacy* involves the expected value of the entity's action to its immediate constituencies in economic, political, or social interdependencies. The constituencies support policies and actions in the exchange of their expected values on the constituent's well-being (Dowling and Pfeffer, 1975). The *influence legitimacy* is associated with constituencies' support for the entity since it is responsive to the constituency's larger interests rather than an immediate exchange of value. Exemplar occurrence of this legitimacy is when the organization (or other social entities) includes the constituents in the policy making structure (Meyer and Rowan, 1977). The *dispositional legitimacy* is related to the constituent's support for the entity when the entity shares their values and interests.

Ⅲ. Research Methodology

The constant comparative method of grounded theory (Glaser and Strauss, 1999) is used with the retroductive approach (Kieser, 1994). The constant comparative method with retroductive approach is appropriate for investigating complex phenomena where no previous research is present (Yin, 1994). Retroduction is useful in examining empirical events over time to identify the underlying mechanisms that could have logically generated the empirical events (Volkoff and Strong, 2013). Since technology-led organizational change is a product of the social structure, the agent's actions, and technologies selected in the past, the best way to understand the change process is by taking a historical retroductive approach (Collier, 1994; Kieser, 1994).

We analyzed two cases. One is INSU and the other is INC. Both companies are in the same conglomerate. Both started an AI-led DT project after top-down direction from the conglomerate's president. While INSU had two years of pilot AI project experience, INC did not have any pilot experience. Data were collected from interviews, project documents, and trade articles. The interviews were conducted with key individuals in TFT (<Table 1>, <Table 2>). Each interview was held separately. Interviews were guided by a facilitator for approximately one hour each.

According to the interview protocol, the interviews were processed by explaining the research objectives to the interviewees. Although the objective of the interview was to investigate how organizations legitimize AI-led organizational changes, we guided the discussion to talk about the distinctive activities and issues related to resource acquisition and organizational support during AI-led DT projects for structuring the discussion. Therefore, the main topics discussed during the interview were as follows:

- Distinctive activities performed at each phase of an AI project
- Reasons for the distinctions
- Issues raised at each phase
- Actions taken to resolve the issues

Data analysis was conducted using the constant comparative method of grounded theory (Glaser and Strauss, 1999). By analyzing the data, we derived the legitimacy required to perform the activities as well as manage the issues throughout the project phases. Data analysis is presented in section 5 after the case descriptions.

Several tactics were used to improve methodological rigor. We reviewed extant literature ranging from institutional theory to AI to identify potentially important constructs. Then, the concepts were used

<Table 1> Interviewee Information of INSU

Team	Informants	No. of Interviews
Bigdata TFT PM	1 manager	2 (21.12.10, 21.12.17)
Bigdata TFT Data Analysis	3 analysts	3 (22.01.03, 22.01.05, 22.01.10)
Bigdata TFT Data Engineer	1 engineer	2 (22.01.11, 22.01.13)
Bigdata TFT AI Platform	1 engineer	2 (21.12.10, 21.12.17)
Digital Innovation	1 manager, 2 employees	2 (22.01.18, 22.01.20)
Product Development	1 developer	2 (22.01.18, 22.01.20)
Marketing	1 manager	2 (22.01.18, 22.01.20)

<Table 2> Interviewee Information of INC

Team	Informants	No. of Interviews
Bigdata TFT PM	1 manager	2 (21.12.21, 21.12.22)
Bigdata TFT Data Analysis	1 analyst	2 (21.12.27, 21.12.28)
Bigdata TFT Data engineer	1 engineer	2 (22.01.06, 22.01.07)
HR Department	1 manager	2 (22.01.12, 22.01.14)
HR Department	2 employees	2 (22.01.24, 22.01.25)

to link the collected data to the study question (Eisenhardt, 1989). We also derived detailed research steps and documented the research process in order to improve reliability (Yin, 1994).

Ⅳ. Case Descriptions

4.1. INSU

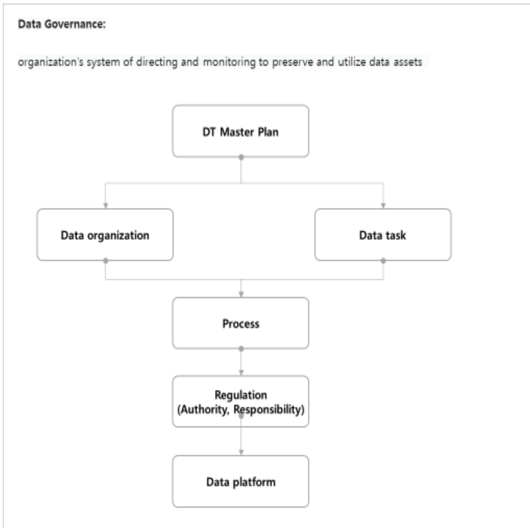
INSU, a consumer life insurance company of the conglomerate, formed its DT team in 2019 when top-down direction from the conglomerate's president for DT was announced. The level of DT (# of DT case) was set for a major KPI of the firm. The impact of AI on the insurance industry is well known due to the citation of Yuval Harari about the Oxford study on 'The Future of Employment (Frey and Osborne, 2013)' in his best-selling book *Homodeus: A Brief History of Tomorrow*: there is a 99% chance of insurance workers losing their jobs from the algorithm around 2033 (Harari, 2017).

From 2019 to 2021, INSU worked with universities to develop ML (machine learning)-based prediction models for insurance fraud and consumer's contract termination. However, the collaborative efforts with universities did not lead to service launching. While INSU was doing pilot projects, there was a strong demand within INSU that data should be standardized, recorded, and managed in accordance with the standard in order to move from AI experiments to AI-based service launching.

In 2021, INSU decided to proceed with the introduction of AI-based services with help from an IT service firm. The target service includes the service to sales agents for automatic (insurance) product recommendations to customers based on the ML model developed using customer data. A TFT was formed with the IT service firm in 2021 by drafting members from the DT team. The business experts in TFT are from INSU's digital innovation, product development, and marketing departments.

The collaboration with the IT service firm was initiated by INSU because INSU needed data infrastructure for ML training and operation. The management of INSU fully understood that customer data is not stored properly and is scattered in various places, and that data standardization is quite insufficient. During the data reviewing process before ML algorithm training, the IT service firm found the INSU's data quality problem and drew up a 'to-be plan' for data governance (<Figure 1>).

At the mid-term project review meeting, it was reported that resolving data quality issues requires establishing data governance within the organization, including big data platform (with database, data warehouse, data lake, analytical tools and visualization tools), new roles and responsibilities, new processes, and new personnel recruitment. Top management



<Figure 1> Data Qovernance Established in INSU

and personnel in the related departments attended the meeting. During the meeting, INSU's top management expressed their strong will for establishing a data platform and data governance.

Fortunately, the top management strongly endorsed on the execution of the data governance plan and allowed them to hire new personnel to work on the critical roles needed in the data governance: collect data regularly, verify whether the data meets standards, and reflect the data on the model. The data governance proposal endorsed by the top management empowered the members of the organization to actively participate in the introduction of the big data platform and the change of work methods. The IT planning and DT Innovation teams in INSU completed the implementation of the data governance by the end of the DT project. The data governance was considered to lay the foundation for DT based on full-scale data analysis in the future.

After seven months (of which two months were spent to enhance the AI competency of the personnel in the project team), the service was launched. The ML model provides sales agents with automatic (insurance) product recommendations for customers based on customer patterns. As this model is applied to sales agents' sales systems, sales agents can skip the existing processes of searching for insurance products and reflecting their own judgment before recommending the products to customers. When the customer's gender, age, region, occupation, etc. are entered in the ML model, the most ideal insurance plan is provided.

4.2. INC

INC is an IT service subsidiary within a conglomerate. INC has around 700 employees and its core customers are financial companies. There was a push for the introduction of DT throughout the conglomerate at the level of the president. Since the level of DT is set as a KPI of each firm of the conglomerate, it was necessary to introduce DT with the intention of business improvement.

With direction from the CEO of INC, the IT department was looking for a task to which AI technology can be applied as an exemplary DT project. Recently, the resignation of employees with less than 5 years of service was about three times higher than before, which is a serious problem. In 2020, led by the IT department, a DT project was started to improve the human resource (HR) problem by developing an ML-based predictive model that can detect and monitor potential retirees in advance. The main purpose of the DT project is to develop an active care program, such as counseling the related employees for grievances when identifying signs of resignation.

At the beginning of the model development, finding an analysis task to solve a business problem and preparing data to develop the predictive model, required active HR participation. However, HR was reluctant. Once the predictive model was developed to classify employees who are likely to quit, it was necessary to verify how accurate the developed model is in the real environment. Along the model validation, HR policy to handle potential retirees should be developed that can be applied once the model is in use. However, HR was not cooperative.

At the mid-term project review meeting, top management promised to continue its support for the project. After the mid-term, HR started to work cooperatively with IT in revising the model. However, the DT project did not move to the service stage where the model is applied to HR operation because of the lack of HR policy.

Ⅴ. Data Analysis

The results of the data analysis are presented in <Table 3> for INSU and table 4 for INC. Based on the constant comparative method, data analysis consisted of several overlapping steps of reading and coding the interview transcripts, re-arranging the codes to better represent concepts (Glaser and Strauss, 1999; Holliday, 2007; Pettigrew, 1990).

First, we each transcribed the interviews and read them several times, extracted basic units of text (words, phrases, or sentence) from the transcripts, and categorized them into four groups coded as 'phases of organizational change', 'challenges and issues' found in each phase, 'actions taken' and types of 'legitimacy type'. The legitimacy type indicates either the legitimacy formed due to the action taken or the legitimacy absent due to no action taken. The codes for the

<Table 3> Coding Categories for INSU's DT Project

Phases of Organizational Change	Challenges/Issues	Actions Taken	Legitimacy Type
DT Initiation			
	Digital transformation throughout conglomerate	- Order by conglomerate's president to start DT projects - Set the levels of DT as KPI for INSU	Regulatory
Pilot Project(s)			
	Facing industry-wide AI-led changes in the insurance sector	Conduct two years of AI pilot projects with universities	Cultural-cognitive
	Running into data quality problems	Agreed to resolve the data quality problems through a collaboration with an IT-service firm as a future project	Normative
Scaling-up			
Model development	Need for developing data infrastructure for model development	Set the development of the data infrastructure for both current and future DT efforts as a specific goal for the collaboration with an IT service firm	Normative
	Need for establishing data governance	Devise plan for the data governance	Normative
Mid-term Project review	Execution of the data governance plan	Obtain support from the relevant personnel and executives for establishing the data governance	Normative; Regulatory
Process change	Process change according to data governance and data platform	Create new roles and responsibility; and recruiting and empowering new personnel	Normative
Service launching and Stabilization			
	Use of the AI service by business departments as daily practice	Hold training sessions and promotion events	Pragmatic

legitimacy types are regulatory, normative, cultural-cognitive and pragmatic types. Those were derived from the literature review.

The phases of organizational changes are DT initiation, pilot stage, scaling-up (including model development, mid-term project review and process change), and service launching and stabilization. We defined scaling-up as rolling AI systems out organization-wide involving integration with existing systems and processes (Davenport and Ronanki, 2018). After scale-up is achieved, the next step is stabilization to improve productivity of the AI system through

<Table 4> Coding Categories for INC's DT Project

Phases of Organizational Change	Challenges/Issues	Actions Taken	Legitimacy Type
DT initiation			
	Digital transformation throughout conglomerate	- Order by conglomerate's president to start DT projects; - set the levels of DT as KPI for INC	Regulatory for INC
	DT not being set as KPI for HR	- Resist by HR department	Lack of regulatory for HR department
Pilot Project(s)			
	No pilot project	No action	Lack of cultural-cognitive within HR department
Scaling-Up			
Model development	HR project being selected by IT department		Lack of normative in HR department,
	Lack of communication with HR department		
	Difficulty of locating HR data		
	Difficulty of developing model		
	Lack of HR policy aligned with the purpose of AI model		
Mid-term Project review	Revising the predictive HR model through the support from HR department	Obtain cooperation from HR department for revising the model; and obtain executive's continuous support	Normative; Regulatory
Process change	The project ended after model revision	Delay the development of data governance and data platform as future projects	
Service launching and Stabilization			
	Not able to move to this stage		

the number of users.

The process for reaching inter-coder reliability of a desirable level included individual coding, followed resolving the differences through discussion. An overall agreement rate between the coders is 92%. <Table 3, 4> show coding categories used in the analysis.

Ⅵ. Research Findings

6.1. Regulatory Legitimacy

Regulatory legitimacy was found to be important to start DT project. The explicit directives from the conglomerate president for DT and DT KPI being set for both INSU and IT-Serve were important to start DT projects. According to the project manager of the IT service firm working on the INSU project:

"we formed a TFT with INSU. Key personnel who have the desire to learn new technologies and who can successfully promote them are directly selected from INSU by its division manager. This was a very rare case. Because this project was linked to INSU's KPI, it was a project that was very closely related to the performance of the division managers. Otherwise, it was not possible to receive unprecedented support for key manpower allocation and infrastructure setting. TFT members who were new to AI were trained by assigning external experts. This preparation process took about two months."

For INC's DT project, there was a problem with relating INC's KPI to the HR department's KPI. Although DT KPI was set for INC, DT KPI was not set for the HR department. This means the lack of regulatory legitimacy for the HR department. There was no motivation for DT. There was no narrative for any pilot AI project within the HR department.

6.2. Cultural-Cognitive Legitimacy

In the case of INSU, the cultural-cognitive legitimacy for pilot AI projects was sufficient. To secure the firm's competitiveness, indispensability of AI adoption was well recognized by the global insurance industry in general as well as INSU itself. Before scaling-up, INSU had two years of pilot AI projects with universities.

We found INC did not have any pilot project in the HR domain. Thus, we conclude that there lacked cultural-cognitive legitimacy for an HR AI project.

6.3. Normative Legitimacy

6.3.1. Model Development

While INSU was doing pilot projects, there was a strong consensus within INSU that data should be standardized, and that data should be recorded and managed in accordance with the standard in order to move from AI pilot experiments to AI-based service launching. The consensus on the needs of a right data infrastructure provides normative justification for the collaboration with the IT service firm. Thus, INSU's business departments who own the data were cooperative with the IT service firm throughout data collection and model development. According to a data engineer of the IT service firm,

"INSU wanted to discuss with us on how data should be standardized, accumulated, and managed from both process and system perspectives. Thus, it can be said that there was active support from INSU's departments involved in the process, and we were able to draw up a 'to-be plan' for the big data platform."

In INC case, DT project was initiated not by the

HR department but by the IT experts. Therefore, there lacked normative legitimacy for the HR department to co-develop the HR predictive model with IT department. As a result, it was difficult for the IT department to communicate with the HR department throughout the model development process. According to the project manager,

"It was a project to contribute to reducing the number of people leaving the company by developing an analytical model using human resources data. We needed active participation from the HR department but they didn't seem to think the model development was their job. Above all, the process of finding business problems and defining them as hypotheses were very difficult tasks for the project team members who studied only the technology to introduce DT without knowing the business at all."

6.3.2. Mid-term Project Review, Process Change, and Service Launching

While fixing data quality problems became a basis for INSU to initiate the project, at the mid-term project review meeting it was reported that resolving data quality issues requires establishing data governance within the organization, including big data platform, new roles and responsibilities, new processes, and new personnel recruitment. Top management and personnel in the related departments attended the meeting. During the meeting, a consensus on establishing data governance including a data platform was made and INSU's top management support was ensured. As results, in the middle of the project, INSU could establish a socially accepted normative system with a data platform, new roles and responsibilities, and new work processes. The new role includes collecting data regularly, verifying whether the data meets standards, and reflecting the data on the model. This new role played a critical role during the model operation and service launching. According to the data engineer from the IT service firm,

"The key to this project was that data should be standardized, regularly collected, and continuously reflected in the AI model. In order to do that, a big data platform must be a prerequisite, and each related department must carry out their work in line with the idea of the big data platform. Fortunately, the strong will of management enabled the members of the organization to actively participate in the introduction of the big data platform and the change of work methods. I think this is a very lucky case compared to other normal projects."

As the project neared the end, INSU was able to complete the establishment of the data governance as well as big data platform. Both the data governance and data platform laid the foundation for INSU's DT.

In the case of INC, despite the difficulty of model development, top management attended the mid-term project review meeting and continuously supported the DT project. After the mid-term review, the HR department and IT department worked cooperatively and revised the predictive model. However, the DT project did not move to the service stage where the model is applied to HR operation. The reasons are expressed in the following interview with the project manager:

"When the analysis results are reported to the management, they were amazed to realize many things they did not know. For example, when a child is born, there are more male employees than female employees who quit their job. I think that the result was used for the purpose of knowing in advance who will likely resign or not. The original purpose was to provide more attention and care to

employees who have experienced similar events or have shown similar behavior patterns to those who left the company. However, the analytical results were not properly utilized in that way.
The copyright of the analytical model was registered. However, it was ended as a pilot case of a DT project."

On-going model updates requires continuous data supply and assurance of data quality. This in turn requires data governance and a data platform. The data governance including the data platform was left as future work for INC.

6.4. Pragmatic Legitimacy

Instead of targeting to replace employees with AI, INSU's DT project was targeted to AI-based insurance coverage analysis which intended to reduce tedious, manual tasks of the sales agents and product development teams. This provides pragmatic legitimacy for the sales agents. According to the sales manager of INSU,

"As a result of AI service, the burden of the sales agent is greatly reduced. It also makes it easy for even first-time sales agents to adapt to the job.
When the service was introduced, it was not of interest to sales agents. They don't seem to be able to easily give up their way of doing things. Thus, the service was set as default on the initial screen of the sales system. Additionally, activities such as education and promotion events were actively implemented."

During the stabilization phase, management actively enhanced the pragmatic legitimacy for the service through training sessions and promotional events. As a result, the sales agents began to participate in utilizing the system as their daily practice. As the number of users increases, the sales agent's belief in the AI system begins to form.

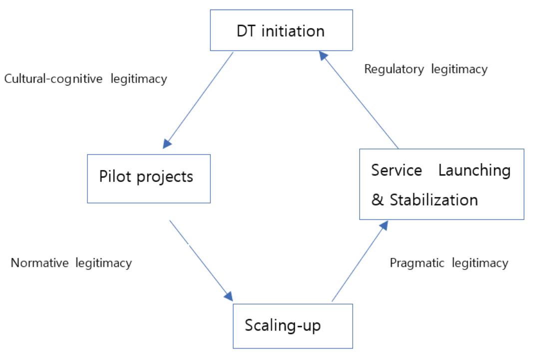
Ⅶ. Discussions and Future Research

The study results indicate that AI-led organization change is not merely technical efforts. For the success of AI-led organizational changes, legitimacy is important for the technical efforts to pay off. The legitimization efforts decrease legitimacy challenges and increase the institutional momentum to progress through the series of phases during the journey of DT. The legitimacy challenges include resistance from organizational members and the difficulty of obtaining necessary resources such as data. As data becomes the most valuable resource for AI model development, cooperation with data owners that are mostly business departments is essential. They are the ones who know the meaning of the data, the insights needed to be derived from the data, and where to locate the data.

Although regulatory legitimacy is important, pressure from executives could result in neglecting the rigorous piloting process. Through the iterative pilot approach with the involvement of the business department, the organization is likely to select an AI application that creates business value. During the pilot process, cultural-cognitive consensus on the selected AI application can also be built, which in turn reduces the challenges of pragmatic legitimacy for the application. Although the culture pressure is beyond the control of one organization (Suchmann, 1995), management needs to make efforts to build cultural-cognitive consensus about the organization's AI strategy through various iterative processes such as pilot projects, workshops, education, and regular interactions.

Through these diverse processes, management can reduce the challenges of normative legitimacy for rolling out the pilot project organization wide. With the clearly shared goal, management can roll out organizational-wide changes by establishing data platform sand data governance with a clear definition of new roles and responsibilities and new business processes. This normative system becomes the basis for the organization's continuous future efforts for DT.

<Figure 2> depicts salient legitimacies required for the INSU to achieve the DT success. In the case of INSU, the industry consensus on the unavoidability of DT were antecedents of the president's directives for DT. The directives became the basis of regulatory legitimacy for firm's DT initiation (i.e., forming DT team, change KPI, etc.). In INSU's case where the cultural-cognitive legitimacy for DT was proper, the regulatory legitimacy further enhanced the firm's momentum to trigger the pilot AI projects. The pilot projects helped INSU to form the normative legitimacy for AI scaling-up. When regulatory, cultural-cognitive and normative legitimacies are proper, the scaling-up was successful. After the success of the scaling up, management enhanced the pragmatic legitimacy of the service to stabilize the change. The cycle in <Figure 2> could be iterative when another IT fashion for DT comes up in the future.

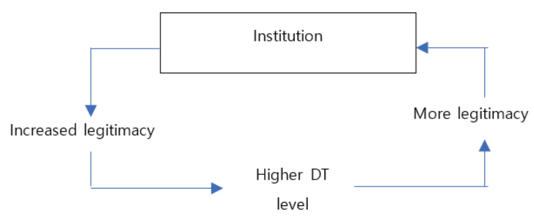


<Figure 2> IpNSU's Path for DT Success

As a future research, <Figure 2> can be re-examined as a series of the following legitimacy enhancing cycle: 1) the increased legitimacy through organization's efforts, enables organizations to proceed through the series of phases of DT; and 2) this in turn reproduces the legitimacy. Repetition of the legitimacy enhancing cycle is likely to increase the chance of DT success.

In the future, the legitimacy enhancing cycle needs to be examined from the perspective a generative mechanism (<Figure 3>); increased legitimacy through organization's efforts enables organizations to proceed through the series of phases of DT, which in turn reproduces the legitimacy. The generative mechanism "has potential to cause an event" (Volkoff and strong, 2013, p. 822) rather than a universal law. Thus, DT success cannot be explained only by the legitimacy enhancing mechanism. Not only are the actualization of the mechanism contingent on other mechanisms but also DT success could have multiple causal paths.

This research can lead to several other directions for future research. The effects of legitimacy of AI adoption on an organization's outcomes such as DT might differ among industy sectors, age of organizations, and AI technology characteristics (i.e., data driven machine leadrning vs. rule-based AI). Thus, the following agenda could be added for the future research: (1) the legitimacy profile for different in-



<Figure 3> Legitimacy Enhancing Cycle for DT

dustry sectors, (2) legitimacy profile for different ages of organizations, and (3) legitimacy profiles for different types of AI can be gathered to view the pattern of legitimacy dynamics as well as the relationships of the profiles. Future research then can be used for legitimacy building and sustaining and repairing an AI led digital transformation.

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◆ About the Authors ◆

Gyeung-min Kim

Professor of MIS in College of Business Administration at Ewha Womans University. She has B.S. in Computer Science at Ewha Womans University and Ph.D. in MIS at Texas Tech University. Her research interests include platform ecosystem, global IS sourcing, and gender issues in IS area. She is a member of Association for Information Systems (AIS) and Korea Society of Management Information Systems (KMIS).

Heesun Kim

Senior manager in Hyundai Autoever IT Service Innovation Team. She has Ph.D. in MIS at Seogang University.

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