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Impact of Quality Factors on Platform-based Decisions

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플랫폼 기반 의사결정 품질 요인의 영향력 연구

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As platforms become primary decision making tools, platforms for decision have been introduced to improve quality of decision results. Because, decision platforms applied augmented decision-making process which uses experiences and feedback of users. This process creates a variety of alternatives tailored for users' abilities and characteristics. However, platform users choose alternatives before considering significant quality factors based on securing decision quality. In real world, platform managers use an algorithm that distorts appropriate alternatives for their commercial benefits. For improving quality of decision-making, preceding researches approach trying to increase rational decision -making ability based on experiences and feedback. In order to overcome bounded rationality, users interact with the machine to approach the optional situation. Differentiated from previous studies, our study focused more on characteristics of users while they use decision platforms. This study investigated the impact of quality factors on decision-making using platforms, the dimensions of systematic factors and user characteristics. Systematic factors such as platform reliability, data quality, and user characteristics such as user abilities and biases were selected, and measuring variables which trust, satisfaction, and loyalty of decision platforms were selected. Based on these quality factors, a structural equation research model was created. A survey was conducted with 391 participants using a 7-point Likert scale. The hypothesis that quality factors affect trust was proved to be valid through path analysis of the structural equation model. The key findings indicate that platform reliability, data quality, user abilities, and biases affect the trust, satisfaction and loyalty. Among the quality factors, group bias of users affects significantly trust of decision platforms. We suggest that quality factors of decision platform consist of experience-based and feedback-based decision-making with the platform's network effect. Through this study, the theories of decision-making are empirically tested and the academic scope of platform-based decision-making has been further developed.

Keywords : Platform-Based Decision Quality, Platform Reliability, Data Quality, User Ability, User Bias

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1. Introduction

Many platforms embedded in digital devices assist decision-making. Individuals choose the most expected decision efficiency value from these platforms. People access platforms through digital devices to help them make direct or indirect decisions when performing daily tasks [37]. Now days, we cannot imagine that delivering packages without information platform which connect between consumer with manufacturer or moving to destination without using Uber platform which connects between drivers and travelers. These platforms help people to make decision to satisfy their needs.

Platforms change an individual's decision-making style and affect digital transformational leadership, in addition to improving employee connectedness for collaboration, innovation [12]. Social platforms have improved relationships between colleagues and customers. New technologies such as mobile devices, cloud computing, and platform applications help top leaders make decisions responsibly [14].

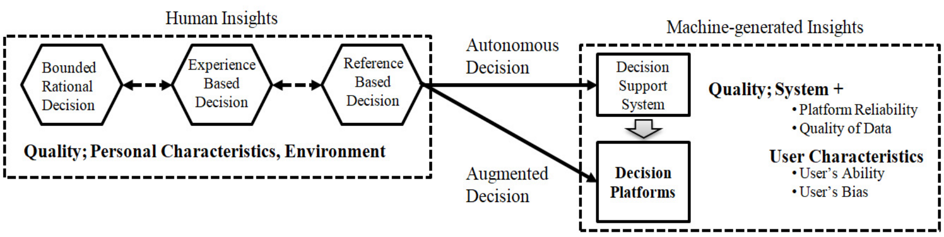
Whenever decision-makers arrive at final managerial judgements, they seek advice from sources, processes to improve judgement accuracy. These fundamentals of decision-making have been developed to enhance the quality of decision results. As shown in <Figure 1>, decision-makers believe that a highly developed autonomous process can create a process by developing machine-aided decision-making algorithms. Autonomous process uses data comprising experiences and feedback from previous users.

However, people use decision platforms more often when making decisions regarding real world problems. This is because autonomous decision-making process regards individual characteristics as a noise in reaching optimal decision results. In actual situations, personal abilities and biases enable the choice of open alternatives, even if they are not optimal for other users. These features of decision platforms increase trust in the decision-making process.

Individuals use a platform-based decision-making process and are aware of its significance. However, they do not consider the quality factors of platforms. Occasionally, platform managers use algorithms to interrupt users' appropriate decision-making processes for their own benefit. For example, recommendation algorithms of online shopping malls present products for commercial advertising, even when people do not have good experiences or feedback [36]. By confirming the quality factors of the platform based decision-making process, we can ensure the quality of decision-making results. Therefore, we need to focus on the quality factors to secure trust in decision platforms.

Quality dimensions have been studied to enhance the quality of decision-making results. The objective view included fact-, logic-based decisions. The subjective view included a personal vision-focused hip-driven decision [37]. Three user quality dimensions - psychological, personal, and environmental - are considered [33]. Systematic and user-characteristic dimensions for augmented decision-making processes are considered [22]. From studies, we chose two systematic and two personal characteristic dimensions as the main quality factors.

However, empirical studies on the quality factors of decision considering platforms are insufficient. Most studies have shown that in decision-making process from rationality of decision makers to machine interaction with autonomous systems or advanced algorithm [3, 7, 11, 13, 20, 28, 33]. Researchers suggest that quality factors of system, data are important factors of improving quality of decision results [1, 8, 9,12]. Because they focused on one-way decision-making process which associate supply chain from supplier of decision support service to decision makers. In the real world problems, however, strategies about proposal of one-way alternative seemed to be failed. Because people rely on multiple decision platforms which provide variety of alternatives [15, 42]. Therefore, decision platforms grasp the characteristics of platform based decision-making. Researches on the competency



<Figure 1> Development of Decision Platforms Including Quality Factors

and bias of users are rare, and these articles focus on ease of use or usefulness of systems [29, 30]. This study attempted to find and validate research questions on key quality dimensions, including characteristics of decision platform. We conducted an empirical quantitative study using multiple platform quality factors to change the decision-making process. First, we focused on platforms as expanded decision support system. Systematic quality factors of the decision platforms evaluated in terms of reliability and quality of data. Second, we emphasized the user characteristics consisting of network effects. We regarded the ability and bias of users as impact factors.

2. Literature Review

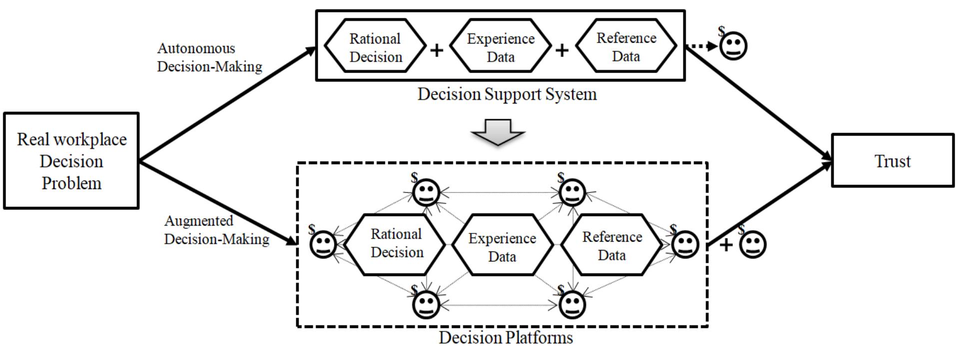
As shown in <Figure 2>, experience and feedback facilitate rational decision-making. Experience-based decision-making uses the ‘intuition’ of decision-makers. Harvey et al. [20] reported that experience enables the decision-makers to improve their ability to attain their goals in decision-making tasks. For example, customers consider data to be a successful purchase experience during online shopping. Kim et al. [23] suggested that the experience data is positively related to trust. Omarli [33] insists that experience-based decisions refer to individuals making decisions based on their skills, knowledge, and training. Bearden and Etzel [6] considered that feedback-based decision-making follows other results as a reference for similar situations. Under the influence of references on individuals’ purchasing decisions, reference information helps them make satisfactory decisions.

According to bounded rationality theory, the ability of human to consider alternatives is limited in storing information and maintaining the process. However, a machine-aided decision-making process is more capable in both cases. It is an interactive system that combines the intellectual resources of individuals with the capabilities of computers to improve decision quality. Higher level of trust in algorithmic advice influence more final judgement than in human advice [20].

Automated decision-making eventually leads to augmented decision-making. Araujo et al. [3] suggest that people with more knowledge are more optimistic about the usefulness of automated decision-making. Although autonomous algorithmic agents control the decision process, the decision-maker can intervene in or override the decision process. Dietvorst et al. [13] reported that machines may provide accurate alternatives for decisions, decision-makers feel comfortable when they can modify the decision-making process.

Currently, decision platforms aid users in their decision-making processes. To complement this, Keding and Meissner [22] suggest a concept of augmented decision-making. The decision systems optimized alternatives for efficiency of decision-makers. In contrast, decision platforms increase alternatives by concerning algorithms, data from users. Burton et al. [7] suggested algorithmic decision-making as a process for utilizing accurate and discriminatory algorithm-based insights as an augmented decision-making process. Demetis and Lee [11] reported that advisory prediction which generated from the decision results of the algorithm-based process can address uncertainty.

With decision systems working autonomously, in the form of autonomous agents or advice platforms that support decision-making process [28]. It focuses on artificial intelligence-based recommendations based on the collected data, knowledge. Formalizing human decisions in an algorithm-based manner and providing output in a transparent and interpretable manner are critical [3]. Gupta et al. [19] reported that artificial intelligence capabilities contribute to



<Figure 2> Platform-based Decision-making Process with Network Effect

<Table 1> Measured Variables and Literature Reviewed

Categories	Latent Variables	[Codes] Sub-Latent Variables	Related Studies
Systematic Factors	Platform Reliability	PR1: Corporate reputation PR2: Operation capability PR3: Effective experience PR4: Recommend accurate decision	Castillo-Soto and Baker [9] Venkatesh et al. [41] Dery et al. [12] Warhurst et al. [43]
	Quality of Data	QD1: Data usability QD2: Interpretability of data QD3: Timeliness of data QD4: Accuracy of data	Gefen et al. [17] Cai and Zhu [8] Alwan et al. [1]
User Characteristics	User's Ability	UA1: Ability to search information UA2: Ability to understand advice UA3: Ability to judge circumstance	Sussman and Siegal [40] Knijnenburg et al. [27] Spetzler et al. [38]
	User's Bias	UB1: Recency bias UB2: Outcome (short-term) bias UB3: Bandwagon effect bias	Baron and Hershey [5] Arnold [4] McNamara et al. [31] Pitoura et al. [35]
Decision Making Quality	Trust	TRST: Count on platform's decision to get important decisions from the platform	Davis [10] Gefen et al. [17] Marth et al. [29]
	Satisfaction	STF: Satisfied with platform's support, decision results, and experiences	Spiteri and Dion [39] Wang and Wang [42]
	Loyalty	LAT: Continued use intention and satisfaction affects recommendation to others	Dittes et al. [14] Kim [24] Mas-Machu et al. [30]

decision-making which helps determine, judge, and decide the course of action for conducting business. Decision platforms have a two-sided characteristic that connects suppliers and customers due to a network effect [34]. Owing to the network effect of platforms, decision platforms exhibit different properties. As the influence of the network effect increases, more alternatives are obtained. Gregory et al. (2021) supported that a considerable amount of analyzable data collected from the experiences and feedback of similar user group [18]. We shortly describes in <Table 1>.

In contrast, autonomous decision systems use collected data, analyzed experiences, and feedback in a step-by-step manner. The systems obtain alternatives by confirming with the decision-makers; this is time-consuming even though it is titled as a real-time system. However, decision platform instantly creates alternatives using augmented processes. Nasseef et al. (2022) reported that the role of decision-makers is to set objectives, accept platform advice, and select an alternative [32].

On the other hand, decision-making accompanied by risk evaluation is not a business process in uncertain environments. Kline (2015) insisted that recognition-primed decision-making model explained that decision-makers did not compare lists of options but a single course of action script in an urgent situation [26]. In addition, decision platforms frequently require commercial intervention. For example, Eslami et al. [15] studied that shopping platforms intend to suggest products shown first, which pay to platforms, even when they do not have experienced or have feed-backed algorithms. Biased algorithms induce a platform's intent to insist on one of the platform alternatives.

3. Research Design

Decision-makers need to consider quality factors before accepting advice. Individuals evaluate their interactions with algorithms by prioritizing their understanding of the purpose. Researches suggest that increased cognitive load may impede one's ability to integrate advice with one's own judgement. Studies have explained quality factors by considering the systematic characteristics of platforms and the abilities and biases of platform users.

3.1 Quality Factors of Decision Platforms

3.1.1 Reliability of Platform

The human-computer interaction through platforms becomes usual, such as electronic document management system through cloud computing technology. Among the characteristics of information systems, the reliability of system and reputation of company have studied extensively, and are the expressive ability of the platform as important factors [41]. For example, when designing platform based decision processes, users' behavioural rules, principles, and standards are declared before activating the platform. Warhurst et al. [43] studied that how reputation of Uber platform increased and affected to users. They studied recommend accurate drivers to platform users. Once the platform's reputation is formed, it attracts consumers and generates more experience and feedback about recommending each group. Therefore, it affects both drivers for living and guests who use this service.

When users access decision platforms, reliability of platform is one of priority quality factors. Decision platforms need operation capability for continuously connecting and sharing. For example, Castillo-Soto and Baker [9] studied information workplace platform (IWP) which has functionality with managing electric document via cloud systems. The IWP insists sharing and collaborative working with accountability to workplace users. In addition, decision platforms show that platforms gave users accurate information to obtain effective experiences. The examples of IWP and Uber describe trust and satisfaction from decision platforms. Also, effective experiences affect employee connectedness and responsive leadership as key factors [12]. In this context, the reliability of a platform requires its operational capability to make an appropriate final decision.

3.1.2 Quality of Data

Data quality can be subdivided into several sub-concepts. Big Data quality dimensions include availability, usability, reliability, relevance, and presentation quality [8]. Accuracy, timeliness, consistency, and completeness are the four dimensions in large-scale cyber-physical systems [1]. As the scope of research is limited to the decision platform and its data quality, we can choose four key characteristics: usability, interpretability, timeliness, and data accuracy.

3.1.3 User Abilities

Although outstanding decision-supporting platforms exist, factors of user characteristics regarding users' abilities are important. Users' abilities to search for information and understand advice are important during the usage stage. After platform user experience, the suggested advice is appropriately connected to the final decision [27]. Decision quality requires a user's ability to judge circumstances. Users can create an appropriate frame and alternatives and commit to an action [38].

3.1.4 User biases

Decision patterns have changed from principle to prevention and creation, and from subjective to objective. Decision quality is important because of its high level of uncertainty [37]. However, decision-makers suffer from personal biases, such as recency, outcomes, and bandwagon effect. When making decisions, users are influenced by the decisions of others in the group to which they belong [35]. Recency and outcome biases also impact non-optimal decisions because users' decisions flow from other people's experiences and feedback [4, 5].

3.1.5 Explaining Decision Quality by Trust, Satisfaction, and Loyalty

With the development of human-platform interactions, decision-making processes have been changing. The representative references are the technology acceptance model (TAM) [10, 17] and extended expectation-confirmation model (eECM) [42]. The TAM explains the behaviour of users such that the perceived usefulness and ease of use of the platform are regarded as variables that influence trust. Data usability positively influences user trust and loyalty [17]. Currently, platforms require trust-quality aspects between service providers and users in terms of responsiveness, legal protection, and tangibility [30]. Trust reduces the perceived risk of sharing information while using a platform, even when users do not know each other personally [29]. Trust in the decision platforms significantly affects customer satisfaction and continued-use intentions. Customers are satisfied if their expected attributes meet the performance criteria. Continuance intention is related to confirmation, satisfaction, and loyalty [39].

3.2 Research Hypotheses and Model

The reliability and reputation of platforms are important systematic factors [41]. Moreover, data quality consists of several dimensions such as expression interpretability, usability, timeliness, and content accuracy. Data quality determines data utilization on the platform and influences trust.

Hypothesis 1: The systematic factors positively influence trust.

Hypothesis 1.1: Reliability of platform positively influences trust.

Hypothesis 1.2: Data quality positively influences trust.

Users make judgements based on non-digital factors with platform support. Decision quality improves as user expertise increases [40]. Therefore, the ability to search for information in platform, understand the platform's recommendations, and judge situation affects the quality of platform based decisions. User biaes affect decision-making results because users follow experiences and feedback of other users in similar group. Network of decision platform increases, more information is gather which users can use. It leads to better quality of decision results. Therefore, users update recency information to increase their network like social network service [15]. Decision-makers try to measure outcomes to determine the value of platforms and decide on investments [5]. The degree of decision-making bias was measured when disclosing or not disclosing the ranking information of other people's decision-making matters. This could be explained by bandwagon effects [31].

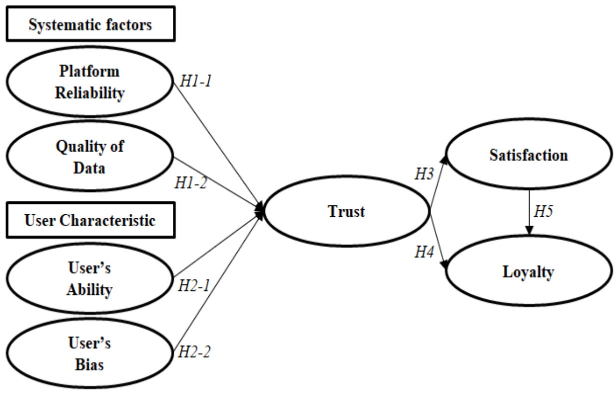
Hypothesis 2: The users' characteristics positively influence trust.
Hypothesis 2.1: User abilities positively influence trust.
Hypothesis 2.2: User biases positively influence trust.

The case of self-centeredness was positive, and the advice provided by the platforms was accepted. The trust of platform users is an essential factor in inferences regarding decision-making in studies. According to the eECM model, trust in a platform has a positive relationship with user satisfaction [42]. User satisfaction affects the continuous use of the platform and provides recommendations to others. Satisfaction affects user loyalty to a platform [24].

Hypothesis 3: Trust positively influences satisfaction.
Hypothesis 4: Trust positively influences loyalty.
Hypothesis 5: Satisfaction positively influences loyalty.

The latent variables are structured in the form of a system of equations. We created a structural equation model (SEM), as shown in <Figure 3> [16, 21]. We selected systematic factors to quantify the data to assist in distinguishing the latent variables.

User characteristics affect the platform's decision results. Platform reliability includes four sub-concept factors: reputation (PR1), operational capability (PR2), effective experience (PR3), and accurate decisions (PR4). Data quality was subdivided into four sub-concept factors: data usability (QD1), interpretability (QD2), timeliness (QD3), and accuracy (QD4).



<Figure 3> Research Model

The user's ability to search for information from the platform's data (UA1), understand the advice (UA2), and judge circumstances based on the decision (UA3) were considered. User biases include recency bias (UB1), outcome in short-term bias (UB2), and bandwagon effect bias (UB3). We selected the latent variables of trust (TRST), satisfaction (STF), and loyalty (LAT) to measure the quality of user decision-making. These variables are not independent because users' trust affects their satisfaction and loyalty. Moreover, satisfaction affects loyalty.

4. Results

4.1 Descriptive Results of the Respondents

We assessed the impact of quality factors on the platform using an online self-assessment survey. Online questionnaires were sent to 430 individuals in November 2021. In total, 391 (90.9%) survey responses were selected, of which insincere or partial responses were discarded (9.1%). The characteristics of specific respondents interpreted in Table 2. Our 391 samples (> 200 samples) were sufficient for analysis by SEM [26].

In order to secure external validity in this study, the ratio of males and females was similar at 48.1% and 51.9%, respectively, in order not to be partial by age, more than 30 survey subjects secured in most age groups of respondents, except thirties. For finding frequency of using platforms, we asked 4-point questions as using decision platforms everyday (almost always), more than one time in a week (to a considerable degree), more than one time in a month (occasionally), or

<Table 2> Descriptive Demographic Results of the Respondents

Characteristics	Category	Total		Student		Office worker		Self-employment		Etc	
		(n=391)	%	(n=95)	%	(n=212)	%	(n=30)	%	(n=54)	%
Sex	Male	188	48.1%	44	11.3%	115	29.4%	13	3.3%	16	4.1%
	Female	203	51.9%	51	13.0%	97	24.8%	17	4.3%	38	9.7%
Age	10~19 years	73	18.7%	72	18.4%	1	0.3%		0.0%		0.0%
	20~29 years	76	19.4%	23	5.9%	41	10.5%	6	1.5%	6	1.5%
	30~39 years	76	19.4%		0.0%	66	16.9%	2	0.5%	8	2.0%
	40~49 years	82	21.0%		0.0%	56	14.3%	9	2.3%	17	4.3%
	Over 50 years	84	21.5%		0.0%	48	12.3%	13	3.3%	23	5.9%

<Table 3> Descriptive Frequency Results of the Respondents

Characteristics	Category	Total		Almost Always		Considerable Degree		Occasionally		Seldom	
		(n=391)	%	(n=329)	%	(n=32)	%	(n=9)	%	(n=21)	%
Sex	Male	188	48.1%	149	38.1%	23	5.9%	5	1.3%	11	2.8%
	Female	203	51.9%	180	46.0%	9	2.3%	4	1.0%	10	2.6%
Age	10~19 years	73	18.7%	68	17.4%	4	1.0%	0	0.0%	1	0.3%
	20~29 years	76	19.4%	64	16.4%	10	2.6%	2	0.5%	0	0.0%
	30~39 years	76	19.4%	71	18.2%	4	1.0%	0	0.0%	1	0.3%
	40~49 years	82	21.0%	69	17.6%	5	1.3%	1	0.3%	7	1.8%
	Over 50 years	84	21.5%	57	14.6%	9	2.3%	6	1.5%	12	3.1%
Job	Student	95	24.3%	87	22.3%	7	1.8%		0.0%	1	0.3%
	Office worker	212	54.2%	179	45.8%	18	4.6%	6	1.5%	9	2.3%
	Self-employment	30	7.7%	22	5.6%	2	0.5%	2	0.5%	4	1.0%
	Etc	54	13.8%	41	10.5%	5	1.3%	1	0.3%	7	1.8%

seldom. The number of people who frequently used decision platforms almost always was 329, accounting for 84.1%. In detail, every occupation groups answered that they use decision platforms almost always. In <Table 3>, female and male answered decision platforms almost always 46.0%, 38.1%. Teenagers, twenties, thirties respondents answered that they are using decision platforms almost always. However, forties and over fifties respondents show up that they use decision platform seldom.

4.2 Descriptive Statistics of key Latent Variables, Reliability, and Validity

We used IBM SPSS statistics (AMOS 24.0 v) to study the research model. First, descriptive statistics and frequency analyses were performed to eliminate outliers, missing values, and data normality of the major variables. Second, reliability, correlation, and factor analyses were conducted. Finally, using SEM, the fit of the model and the relationship between the independent variables were identified, and bootstrap analysis was performed.

Reliability of platform and quality of data included four sub-latent variables: PR1-PR4, QD1-QD4 respectively. Each user ability and user bias included three sub-latent variables: UA1-UA3, UB1-UB3, respectively. There were three endogenous variables: trust, satisfaction, and loyalty. A frequency analysis was performed to satisfy the assumption of a normal distribution. The skewness and kurtosis of the variables were smaller than 2.0 and 7.0, respectively [44]. Factor analysis showed that all variables were composed of a single dimension, and the number of items was less than five.

Questionnaire items were used as the observational variables, so we analysed correlation between each variable to determine whether unreasonable estimates or high correlations (±0.90). To secure internal validity, reliability values were obtained using Cronbach's α test and internal consistency reliability indicators. Generally, if the indicator is greater than 0.7, the variable measurements are judged to secure internal validity [16]. Most of the study variables exhibited $\alpha \geq 0.7$. Among the user bias factors, we asked whether the variable emphasized the latest information (UB1). Business platform users were the latest sources of information rather than accuracy [17]; therefore, they were rated relatively low at 0.579.

The factors were analyzed to understand the classification of the subfactors as platform quality factors. A dimension-reduction method was used to analyze these factors. The factors were rotated using varimax rotation with Kaiser Normalization and extracted using principal axis factoring. The minimum value of the Kaiser-Meyer-Olkin (KMO) measure was 0.802, and the p-value of Bartlett's test of sphericity was less than 0.05, indicating the suitability of the factor analysis model. The average cumulative variance was 68.98% (min. 55.51%); therefore, the explanatory power of the factors was judged to be sufficient. As shown in Table 4, four were included in the systematic factors, and three were included in user characteristics and endogenous variables. In the commonality value analysis, most values were greater than 0.4, whereas those of UA2-3 (0.394), UB1-1 (0.37), and UB1-3 (0.341) were less than 0.4.

4.3 SEM Analysis Results

First, we analyzed systematic factors except UA2. The chi-square ($\chi 2$) value was 789.468 ($p<.001$), TLI=0.937, CFI=0.947, and RMSEA=0.054; thus, the model was acceptable. However, the factors were eliminated when the p-values of the regression weights were greater than 0.05. The paths from PR4 ($p=0.064$), QD3 ($p=0.847$), and UA1 ($p=0.568$) to trust were eliminated. The chi-square ($\chi 2$) value was 431.002 ($p<.001$), TLI=0.946, CFI=0.956, and RMSEA=0.057. Considering the model's goodness of fit, this was acceptable.

<Table 4> Goodness fit of SEM

Categories	Latent Variables	Measurement Variables	Estimate		S.E.	C.R.
			B	β		
Systematic Factors	Reliability	PR2-3	1	0.888		
		PR2-2	0.915	0.83	0.05	18.239***
		PR2-1	0.705	0.646	0.052	13.572***
	Quality of Data	QD1-3	1	0.849		
		QD1-2	1.009	0.834	0.052	19.228***
		QD1-1	0.93	0.83	0.049	19.115***
User Characteristics Factors	User's Ability	UA3-1	1	0.834		
		UA3-2	1.097	0.824	0.072	15.146***
	User's Bias	UB2-2	1	0.822		
		UB2-1	0.987	0.767	0.075	13.157***
		UB3-1	1	0.621		
		UB3-2	1.506	0.742	0.134	11.208***
		UB3-3	1.523	0.81	0.13	11.725***
Decision Making Quality	Trust	TRST1-3	1	0.654		
		TRST1-2	1.129	0.731	0.089	12.675***
		TRST1-1	1.124	0.793	0.083	13.547***
	Satisfaction	STF1-3	1	0.894		
		STF1-2	0.96	0.877	0.039	24.799***
		STF1-1	0.937	0.87	0.038	24.404***
	Loyalty	LAT1-3	1	0.727		
		LAT1-2	1.082	0.826	0.069	15.565***
		LAT1-1	1.101	0.83	0.07	15.64***

*$p<0.05$, **$p<0.01$, ***$p<0.001$.

<Table 5> Path Analysis of Quality Factors

Path	Estimate		S.E.	C.R.
	B	β		
PR2→Trust	0.174	0.256	0.032	5.47***
QD1→Trust	0.135	0.178	0.044	3.092***
UA3→Trust	0.154	0.192	0.046	3.357***
UB2→ Trust	0.129	0.17	0.045	2.851***
UB3→Trust	0.43	0.354	0.079	5.462***
Trust→STF	1.208	0.911	0.087	13.844***
Trust→Loyalty	0.55	0.467	0.151	3.643***
STF→ Loyalty	0.395	0.446	0.111	3.571***

*p<0.05, **p<0.01, ***p<0.001.

In <Table 5>, the standardized estimates (β) of PR2, QD1, UA3, UB2, and UB3 for trust were 0.256 ($p<0.001$), 0.178 ($p<0.01$), 0.192 ($p<0.001$), 0.17 ($p<0.01$), and 0.354 ($p<0.001$). Therefore, we found that users' expectations of the platform's operational capabilities (PR2) enhanced trust of platform. Data usability (QD1) was also a systematic factor that affected trust. Relationships between users' characteristics and trust exist; users' ability to judge circumstance (UA3), user bias towards recency (UB2) and group decisions (UB3) were the most important factors. The values of trust in satisfaction, trust in loyalty, and satisfaction with loyalty were 0.911 ($p<0.001$), 0.467 ($p<0.001$), and 0.446 ($p<0.001$). The endogenous variables were larger than the exogenous variables, our SEM for decision-making ability was set appropriately. We found that trust affected satisfaction and loyalty, whereas satisfaction affected loyalty as shown in <Figure 4>.

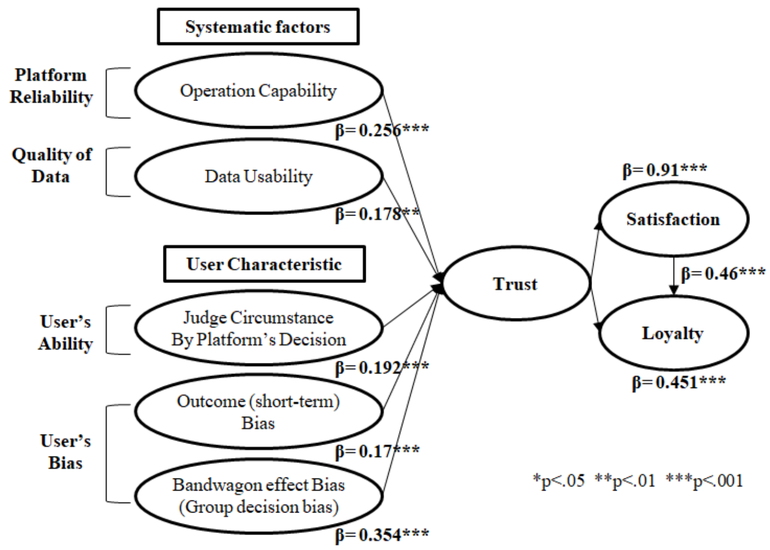
5. Conclusion

We investigated the quality factors affecting platform-based decision-making. An online survey was conducted to validate the research hypotheses and suggest an integrated perspective. We adopted SEM to solve simultaneous equations through causal relationships.

The results explain the systematic factors that significantly affect the quality of decision-making. The platform's operational capability to recommend decisions is positively associated with the quality of decision-making. Reputation of the platform and effectiveness of experience are also significant. Data usability for accessing and using data and the timeliness of data had a more significant impact than interpretability. Regarding the user characteristics, the user's ability to search for information and judge circumstances based on the platform's decision is important when making decisions on decision platform. Although a platform supports decisions, users must enhance their decision-making abilities.

5.1 Quality Factors from Platform Based Decision-making

The bandwagon effect bias exhibited the greatest influence on decision-making quality, reflecting the characteristics of decision platforms. If an organization uses decision platforms, the group decision to which users belong is one of the most influential factors affecting individual decision quality. When the direction of group decision-making decided during work,



<Figure 4> Path Analysis Result

individual work progress and decision-making are conducted with the herding effect of overall opinion. In addition, as short-term performance bias affects trust, the performance of an organization should be measured in the short term because platforms change constantly.

Second, the operational capability of the platform is an important factor. If platforms' operational capabilities are unstable, users can stop the platform based decision process. Changing to other decision platforms would then be challenging because the uncertain decision environment also moves simultaneously. However, this process is time-consuming and expensive.

Third, users can judge circumstances based on the platform's decisions. To ensure customer satisfaction, managers should judge the platform's decisions and describe the information sources used when making decisions. Although the platform has information and supports decision-makers, managers should have the ability judge what types of information are valuable.

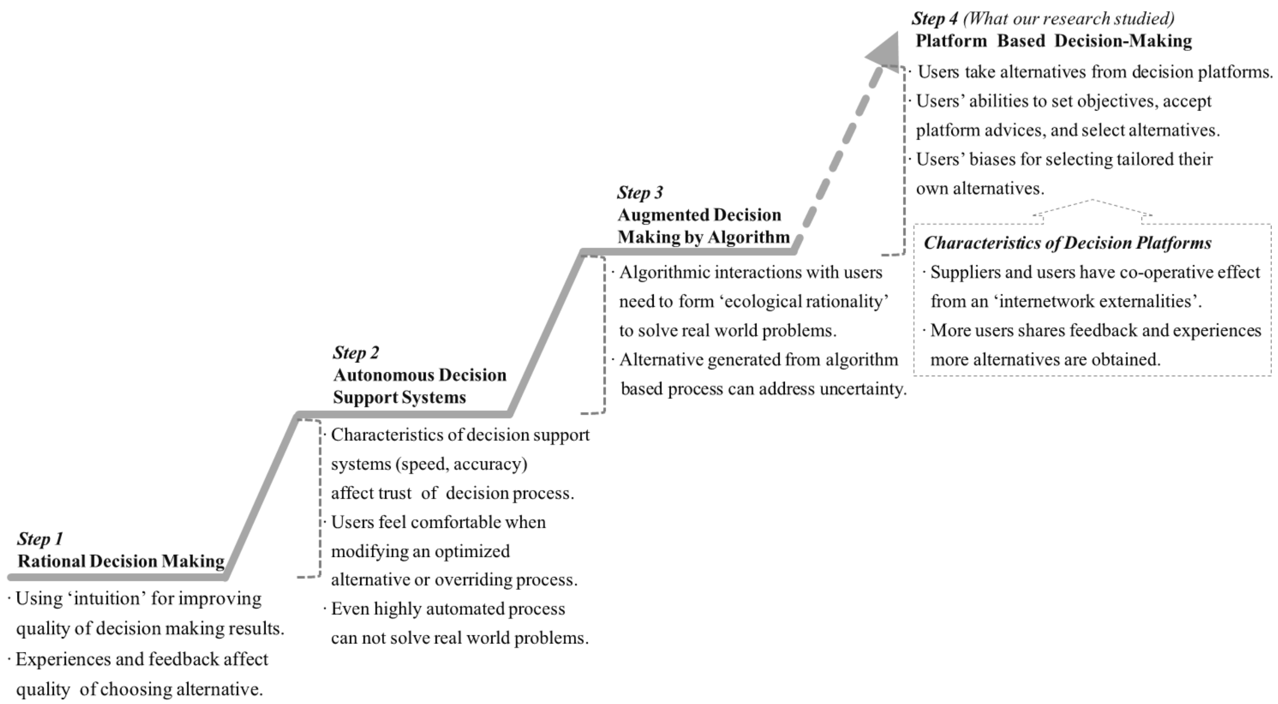
Finally, the usability of the platform's data affects the decision-making quality. It cannot be used if it is difficult to access or obtain information on the platform. Using TAM, we determined the ease of use and usability of the new technology. Nevertheless, decision platforms should be easy to use so that users in an organization can access it and make better use of it for making decisions.

In this study, we aimed to identify the platform factors that impact users' decision-making quality in terms of trust, satisfaction, and loyalty to platforms. These impacts can be numerically compared with the standardized estimate (β) values. Trust has the greatest effect on satisfaction and is greater than the effect of trust with loyalty or satisfaction with loyalty. The results of the studies were validated. Our study addresses the research gaps by seeking to understand the factors that are critical to decision-making quality using decision platforms.

6. Discussion

6.1 Theoretical & Managerial Implications

Our study aimed to identify the quality factors of platforms influencing decision-making. As described in <Figure 5>, while studies focus on decision-making in one-sided market, our study deals with decision-making issue in platform service where user's characteristics plays influential role in decision process as well as quality factors. In decision-making studies,



<Figure 5> Steps to Platform Based Decision-Making

decision support system is a one-way relationship from service producers to consumers presenting sophisticatedly calculated and optimized alternatives. However, in our study, we focused that platform based decision-making process. The process makes data which are produced by users that make up the platform. The data are based on users' interactions with other users and influence outcome of decision. So, we focused characteristics of users which compose experience and feedback data. The decision-making platform addresses application of a decision-making process that utilizes user experience and feedback. Therefore, platform-based decision-making process addresses a variety of alternatives tailored to users' abilities and biases. In this manner, we studied quality factors of decision platforms which were analyzed in terms of systematic factors and user characteristics. Also, based on the survey responses, the impact of platform quality factors on trust, satisfaction and loyalty were quantitatively analyzed.

The main contribution of this study is twofold. Firstly, this study provides an insight on understanding the platform based decision-making and provides a theoretical basis of analyzing quality factors. Platform based decision-making process has different characteristics from traditional process. Because decision platforms have two-side groups with platform management group which consists alternatives suppliers and users. By network effect of decision platforms, more suppliers gather, users can find more easily their own appropriate alternatives on decision platforms. Then more users flow into decision platforms to make experiences and feedback. However, studies about decision-process have not considered platform's characteristics. Studies about quality of platform usually handle with quality of data, reliability of system, and accuracy of algorithms. These studies have not considered decision-making process by users and their characteristics. So, this paper focused a gap of considering the platform user's characteristics, provides an insight to enlarge the understanding of decision-making ecosystem surrounding the platform service.

When it comes to managerial implications, companies can focus on important factors of platform in the workplace. Moreover, contingencies such as operational capability and data usability are important systematic factors that platform builders can control. The fact that 'Bandwagon effect bias' showed highest influence on trust should be noted which clearly indicates the impact of customer interaction on decision process. Therefore, company or platform manager should fully understand the status of interaction between users and provide a strategy to enhance the platform trust. Platforms with limited resources should also focus on these factors. This study will enable other researchers to conduct future quantitative research on platform based decision-making.

6.2 Limitations & Future Research

This study has several limitations. Firstly, since the questionnaire items organized based on a Likert scale, the tendency of respondents may not be reflected accurately. The survey conducted based on the general platform the respondents frequently use, which does not fully consider the type or purpose of the platform. Therefore, further study may specify the type or form of platform to understand the distinctive relationship between platform quality and trust. In the similar manner, since this study dealt with the platform in workplace, the characteristics of platforms in other cases may be analyzed. Furthermore, platform-based decision-making quality changes according to variations. Changing user bias towards the platform may increase trust in the platform. The decision of variation should be investigated in future studies to measure the changes in quality factors.

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<Appendix> Questionnaire Items

<Table A1> Questionnaire Items

Questions	
Systematic factors - Reliability of Platforms	
Reputation of platform service providers.	
1	Platform providers have a positive image.
2	Platform providers deserve respect to their services.
3	Platform providers generally have a good reputation.
Reliability of platform service providers	
4	The platform take cares well about sellers/producers and buyers/users.
5	The platform provides a secure trading system.
6	Overall, platform is reliable to use.
Effectiveness of platform experiences	
7	The experience of using the platform directly is better than expected.
8	The information provided by the platform company is better than expected.
9	By using the platform, the overall requirements are met.
Adequacy of recommendation of platforms.	
10	It can earn revenue and new opportunities by using the platform.
11	It can express my capabilities through the platform.
12	Platform makes feel accomplishment and pleasure by using.
Systematic factors - Quality of Data	
Usability of data	
13	The data on the platform is easy to use.
14	The data on the platform is easy to access
15	Through the platform, I can get information where I expected it to be.
Expressiveness of data	
16	The data on the platform is easy to understand.
17	The data on the platform is well structured.
18	The data on the platform has consistency.
Timeliness of data	
19	The platform has enough information in proper time (Not old information or distance future).
20	The information on the platform reflects the situation of the times (Not historical times).
Accuracy of data	
21	The data provided by the platform is accurate.
22	The information provided by the platform has various perspectives.
User Characteristics - Ability of Users	
Ability to Retrieve Information from Platform	
23	I tend to find the information I want accurately through the platform.
24	I can handle important tasks by searching using the platform.
25	I know search keywords to get the alternatives I want.
Ability to Understand Recommendations	
26	I accurately understand the alternatives provided by the platform.
27	I can practically use the alternatives provided by the platform.
28	I can distinguish between exaggerated or false information.
Ability to Judge Situations	
29	I know what to check to judge quality of alternatives
30	I know sources of alternatives that help me choose the platform.
User Characteristics - Biases of Users	
Recency Bias	
31	I think the latest information is critically considered when making decisions.
32	I usually get information from people who are close and comfortable.
33	I put importance on latest information than traditional theory.
Short-term Performance Bias	
34	Incentives such as coupons provided by the platform affect decision-making.
35	The short-term performance of products and services provided by the platform is better than a distance output.
In-Group Bias (In-Group Favoritism)	
36	I tend to value the opinions of my group when making decisions.
37	I tend to actively refer to other users' reviews.
38	The platform that provides reviews in similar group characteristics of users affects purchase decisions.
Trust	
39	I tend to trust the decision-making alternatives provided by the platform.
40	I tend to use the platform to make important decisions.
41	Decisions through platforms do not lead to the worst results.
Satisfaction	
42	I am satisfied with the decision support provided by the platform.
43	I am satisfied with the decision-making results through the platform.
44	Overall, I am satisfied with the decision-making experience using the platform.
Loyalty	
45	I plan to continue using the platform service.
46	I tend to keep using it once I'm satisfied with a particular platform service.
47	I recommend relatives and acquaintances to use the platform.

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