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Analysis of Information Quality in Management Information Systems in Decision-Making

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KEYWORDS
Information Quality, Management Information Systems, Decision Making, PLS-SEM, Data Accuracy, Information Relevance, Data Governance, Manufacturing Companies

ABSTRACT
This study is motivated by the rapid digital transformation that has increased the strategic role of Management Information Systems (MIS) in organizational decision-making. However, high investment in information systems does not always guarantee better decision quality due to issues related to information quality. Therefore, this research aims to analyze the effect of information quality dimensions accuracy, completeness, timeliness, relevance, and consistency on decision-making quality in Indonesian manufacturing companies. This study adopts a quantitative approach with a cross-sectional survey design. Data were collected from 145 managers and decision-makers in medium-to-large manufacturing companies using purposive sampling. The analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. The results show that all five dimensions of information quality significantly and positively influence decision-making quality, with accuracy as the most dominant factor, followed by timeliness, relevance, completeness, and consistency. The model explains 74.2% of the variance in decision-making quality, indicating strong predictive power. In conclusion, improving information quality is crucial for enhancing decision-making effectiveness. Organizations are recommended to prioritize data accuracy, timeliness, and system integration to support better managerial decisions.

INTRODUCTION

The wave of digital transformation that has swept the global business world has fundamentally changed the way organizations create value, compete, and survive in an increasingly complex marketplace. At the heart of this transformation, Management Information Systems (MIS) have evolved from mere administrative tools into strategic assets that determine an organization's long-term competitive advantage (Laudon & Laudon, 2020). Modern MIS not only automate routine business processes but also integrate data from a variety of internal and external sources to generate insights that support decision-making at all levels of the organization, from day-to-day operational decisions to long-term strategic planning (Akter & Wamba, 2016).

Nevertheless, a paradox often found in managerial practice is that large investments in information technology infrastructure do not always correlate with a proportionate improvement in the quality of decision-making. A study by Petter et al., (2013) reveals that one of the critical factors often overlooked is the quality of information generated by such systems. Information that is inaccurate, incomplete, untimely, or irrelevant can lead to poor decisions, even when the systems generating it are technically sophisticated and expensive.

Indonesia, as one of the largest developing economies in Southeast Asia, is experiencing a significant acceleration in the adoption of information technology in the manufacturing sector. Based on data from the Ministry of Industry (2023), more than 60% of medium-scale manufacturing companies in Indonesia have implemented integrated Management Information Systems; however, preliminary studies show that only 34% of these implementations are considered successful in supporting effective strategic decision-making. This gap indicates a fundamental problem related to the quality of information generated by the system.

Information quality, as a multidimensional construct, has received intensive academic attention since the 1990s. Wang & Strong, (1996), through their seminal study, identified more than 200 attributes of data quality, which were then consolidated into four main dimensions: intrinsic, contextual, representational, and accessibility. This framework has since been adapted and refined by various researchers for the specific context of MIS and managerial decision-making.

Although the information quality literature has developed rapidly, there is still a significant gap in understanding how each dimension of information quality contributes to the quality of decision-making in the context of manufacturing firms in developing countries, particularly Indonesia. The majority of previous research has been conducted in developed countries with different business contexts and organizational cultures; therefore, the transferability of their findings to the Indonesian context still requires empirical verification.

Based on the background described above, several main problems that are the focus of this research can be identified. First, there is inconsistency in previous research findings regarding which dimension of information quality is most critical for decision-making, indicating the need for confirmatory research within a more specific context. Second, there is a lack of empirical research based on primary data that measures the comprehensive influence of all five dimensions of information quality simultaneously using rigorous Structural Equation Modeling (SEM) methodology in the Indonesian manufacturing environment. Third, there is insufficient evidence-based guidance for IT managers and decision-makers in Indonesian manufacturing companies to prioritize investments in improving MIS quality.

This research has four interrelated main objectives. First, to analyze the actual condition of user perceptions regarding the quality of information in MIS used in Indonesian manufacturing companies. Second, to empirically test the influence of each dimension of information quality (accuracy, completeness, timeliness, relevance, and consistency) on the quality of decision-making. Third, to determine the most dominant dimension of information quality in influencing decision-making quality. Fourth, to formulate strategic and operational recommendations to improve MIS quality in alignment with managerial decision-making needs.

Theoretically, this research contributes to the development of an information quality model integrated with decision-making theory in the context of MIS in developing countries. It also expands the application of Partial Least Squares Structural Equation Modeling (PLS-SEM) as an appropriate methodology for analyzing multivariate causal relationships in the information systems domain. Practically, the findings provide evidence-based guidance for executives, IT managers, and system designers in allocating resources for MIS quality improvement that most significantly impacts the effectiveness of organizational decision-making.

This study is limited to medium-to-large manufacturing companies (number of employees > 100) located in East Java and DKI Jakarta provinces that have implemented integrated MIS for at least three years. The respondents are managers and staff with decision-making authority who regularly use MIS in their work. The dimensions of information quality examined are limited to five main dimensions: accuracy, completeness, timeliness, relevance, and consistency.

METHOD

This research adopts a positivism paradigm that emphasizes objectivity, quantitative measurement, and statistical generalization (Creswell, 2014). The quantitative approach was chosen because of its suitability with the research objectives that focus on testing hypotheses formulated a priori based on existing theories. The research design used is a cross-sectional survey design, where data is collected at a single point in time from a representative sample of a specified population.

The study population was all managers and decision-making staff who used driver's licenses in medium-large manufacturing companies (number of employees ≥ 100 people) located in East Java Province and DKI Jakarta, Indonesia. Based on data from the Chamber of Commerce and Industry (KADIN, 2023), there are around 850 companies that meet this criterion.

The sampling technique uses purposive sampling with inclusion criteria: (1) the company has implemented an integrated driver's license for at least 3 years; (2) the respondent is an active user of the driver's license in daily work; (3) the respondent has the authority to make operational, tactical, or strategic decisions; (4) the respondent has at least 2 years of work experience in the current position. The minimum sample size is determined based on the rule of thumb for PLS-SEM which is 10 times the maximum number of predictors in the structural model (Hair et al., 2019), so the minimum sample required is 50 respondents. To increase representativeness and statistical strength, the target sample was set at 150 respondents from 15 companies (10 respondents per company).

The research variables consisted of six latent constructs each of which was measured by reflective indicators. Construct Accuracy (ACC) is measured by 4 indicators that adapt the scale from (Wixom & Todd, 2005): (ACC1) the data in the SIM is error-free; (ACC2) the information presented by the SIM is reliable; (ACC3) The driver's license presents accurate information; (ACC4) information from the driver's license reflects the actual conditions of the business.

Construct Completeness (COMP) is measured by 4 indicators: (COMP1) the SIM presents all the information needed for decision-making; (COMP2) information from the driver's license covers all relevant aspects; (COMP3) The driver's license does not have significant information gaps; (COMP4) the completeness of the report from the driver's license satisfies managerial needs. The Construct of Timekeeping (TIME) is measured by 4 indicators: (TIME1) information from the SIM is always available on time; (TIME2) SIM presents up-to-date information; (TIME3) reports from the SIM can be accessed according to the required schedule; (TIME4) updating information in the driver's license is carried out regularly and precisely.

The Construct of Relevance (REL) is measured by 4 indicators: (REL1) information from the driver's license according to the needs of my task; (REL2) The driver's license presents information relevant to the context of the decision; (REL3) information from the driver's license helps me focus attention on important issues; (REL4) The SIM can be customized to display the information that is most relevant to me. Construct Consistency (CONS) is measured by 4 indicators: (CONS1) information from various SIM modules is mutually consistent; (CONS2) there is no contradiction of information between different reports in the driver's license; (CONS3) definition and format of data in a uniform driver's license; (CONS4) historical information in the driver's license is consistent with the latest report.

The dependent variable, Decision Making Quality (DQ), was measured by 5 indicators adapted from Bharati & Chaudhury (2004): (DQ1) the decisions I made with a driver's license were of better quality than without a driver's license; (DQ2) The driver's license helped me make more targeted decisions; (DQ3) I am more confident in making decisions when using a driver's license; (DQ4) SIM speeds up the decision-making process without sacrificing quality; (DQ5) SIM-based decisions result in better outcomes for the organization.

Data collection was carried out during the March-June 2024 period using a mixed online and face-to-face method. The online questionnaire is distributed through the Google Forms platform to managerial contacts at the sample company, while the printed questionnaire is distributed directly through the company's coordinator. Prior to the full-scale distribution, a pilot test was conducted on 30 respondents from the same population to test the instrument's readability and initial internal consistency. The results of the pilot test showed a Cronbach's Alpha value of > 0.7 for all constructs, so the instrument was declared suitable for use without substantial modifications.

Data analysis was carried out in several stages using two software: IBM SPSS Statistics 26 for descriptive analysis and initial assumption tests, and SmartPLS 3.0 for PLS-SEM analysis. The reasons for choosing PLS-SEM over CB-SEM are: (1) relatively small sample size (145 observations); (2) research objectives oriented towards prediction and exploration; (3) distribution of data that is not assumed to be normal; and (4) models that include formative and reflective constructs (Hair et al., 2017).

The evaluation of the measurement model (outer model) was carried out through: (a) Convergent validity: AVE > 0.5 and loading factor > 0.7; (b) Discriminant validity: HTMT < 0.85 (Henseler et al., 2015); (c) Reliability: Cronbach's Alpha > 0.7 and CR > 0.7. The evaluation of the structural model (inner model) includes: (a) Coefficient of determination R^2; (b) The coefficient of the path and its significance through bootstrapping 5000 subsamples; (c) Predictive relevance Q^2 through blindfolding procedures; (d) The effect of the size f^2; and (e) Goodness of fit through SRMR < 0.08.

RESULT AND DISCUSSION

Characteristics of Respondents

Of the 150 questionnaires distributed, 147 were successfully returned (98% response rate). After the screening and data cleaning process, 145 questionnaires were declared valid and complete for further analysis. Two questionnaires were excluded due to incomplete answers (>10% of blank items). Table 1 presents the complete demographic profile of the respondents.

Table 1. Respondent Demographic Profile (n = 145)

Features	Frequency (n)	Percentage (%)
Gender		
Male	90	62,1
Women	55	37,9
Age		
< 30 years old	28	19,3
30–45 years	85	58,6
> 45 years old	32	22,1
Final Education		
Diploma (D3/D4)	19	13,1
Bachelor (S1)	78	53,8
Magister (S2)	42	29,0
The Doctor (S3)	6	4,1
Departments		
Senior Executive	31	21,4
Middle Manager	63	43,4
Line Manager	51	35,2
Experience using a driver's license		
1–3 years	33	22,8
4–6 years	67	46,2
> 6 years old	45	31,0

Source: Primary data processed (2024)

Demographic data shows the dominance of male respondents (62.1%) with the age group of 30–45 years as the majority (58.6%). The level of education of the respondents was quite high, with 86.9% having a bachelor's degree or higher, indicating the quality of the respondents was adequate to competently assess the quality of driver's license information. The diverse distribution of positions (executives, middle managers, and line managers) ensures that decision-making perspectives at different levels of the organizational hierarchy are well represented in the sample.

Descriptive Statistics of Research Variables

Table 2 presents descriptive statistics for all research variables based on respondents' perception of the quality of SIM information they use.

Table 2. Descriptive Statistics of Research Variables

Quality Dimension	Average Score (1–5)	Category
Accuracy (ACC)	3.92 (SD=0.61)	High
Completeness (COMP)	3.74 (SD=0.68)	High
Punctuality (TIME)	3.61 (SD=0.72)	High
Relevance (REL)	3.85 (SD=0.59)	High
Consistency (CONS)	3.48 (SD=0.77)	Medium
Quality of Decisions (DQ)	3.79 (SD=0.63)	High

Remarks: Categories are based on range: Low (1.00–2.33), Medium (2.34–3.67), High (3.68–5.00)

The average score for all dimensions of information quality ranged from 3.48 to 3.92 on a 5-point scale, indicating that the perception of information quality was generally in the high category. Accuracy scored the highest (M=3.92), while consistency scored the lowest (M=3.48) and was in the medium category. A decision-making quality score of 3.79 indicates that respondents generally feel positive benefits from using driver's licenses in their decision-making process.

Evaluation of Measurement Models (Outer Model)

Table 3 summarizes the results of the evaluation of the measurement model for all constructs in the study.

Table 3. Measurement Model Evaluation Results

Construct	AVE	CR	Cronbach α	Remarks
Accuracy (ACC)	0,684	0,897	0,863	Valid & Reliable
Completeness (COMP)	0,651	0,881	0,841	Valid & Reliable
Punctuality (TIME)	0,673	0,892	0,857	Valid & Reliable
Relevance (REL)	0,692	0,901	0,869	Valid & Reliable
Consistency (CONS)	0,661	0,871	0,829	Valid & Reliable
Quality of Decisions (DQ)	0,718	0,913	0,887	Valid & Reliable

Source: SmartPLS 3.0 Output (2024)

The results of the evaluation showed that all constructs met the criteria of convergent validity with AVE > 0.5, discriminant validity with HTMT < 0.85 for all construct pairs, and adequate reliability with CR and Cronbach's Alpha > 0.7. No measurement problems were found, so the testing of the structural model could be continued with the belief that the research instrument measured what it was supposed to measure.

Structural Model Evaluation and Hypothesis Testing

Table 4 presents the results of testing the research hypothesis through a bootstrapping procedure with 5,000 subsamples.

Table 4. Hypothesis Testing Results (n = 145, Bootstrapping 5,000 subsamples)

Hypothesis	b	t-stat	p-value	f^2	Remarks
H1: ACC → DQ	0,312	4,821	0,000	0,148	Accepted
H2: COMP → DQ	0,198	3,124	0,002	0,072	Accepted
H3: TIME → DQ	0,287	4,413	0,000	0,121	Accepted
H4: REL → DQ	0,264	4,182	0,000	0,107	Accepted
H5: CONS → DQ	0,176	2,987	0,003	0,058	Accepted
R^2 (DQ) = 0.742 | Q^2 = 0.531 | SRMR = 0.057					

Source: SmartPLS Output 3.0 (2024) | *p<0.05; **p<0.01; p<0.001

All five research hypotheses are empirically supported. The structural model shows R^2 = 0.742, which means that 74.2% variance in decision-making quality can be explained by all five dimensions of information quality studied. This value belongs to the 'substantial' category according to the classification of Cohen (1988). Predictive relevance Q^2 = 0.531 confirms the model's adequate predictive capabilities. SRMR values = 0.057 < 0.08 indicate a good model match.

The Effect of Accuracy on the Quality of Decision Making

Information accuracy was proven to be the most influential dimension on the quality of decision-making ($\beta=0.312$, $f^2=0.148$). The magnitude of the effect $f^2=0.148$ indicates the influence of the medium which means substantial in practical terms. These findings are consistent with and reinforce the results of Wang & Strong (1996) which placed accuracy as the most frequently cited information quality attribute by data users as the most important attribute, as well as with Gorla et al. (2010) which documented the dominant influence of information quality on decision-making performance.

The significant influence of accuracy can be explained through the mechanism of cognitive trust. When users perceive the information in the SIM as accurate, they will be more willing to rely on that information as a basis for decisions without the need for time- and resource-intensive external verification. Conversely, a history of data inaccuracies creates a 'trust deficit' that encourages decision-makers to seek information from alternative sources or rely on personal intuition, both of which have the potential to result in worse decisions (Stvilia et al., 2007).

The practical implications of these findings are the need to implement a comprehensive quality assurance mechanism to maintain data accuracy in SIMs, including automatic data validation at input points, periodic data cleansing, data reconciliation between systems, and scheduled data quality audits.

The Effect of Punctuality on the Quality of Decision Making

The timeliness of information ranks second in its influence on the quality of decision-making ($\beta=0.287$, $f^2=0.121$). These findings reflect the reality of Indonesia's increasingly dynamic and competitive manufacturing business, where the window of opportunity for decision-making is often very narrow. Information that is late, although accurate, loses its pragmatic value because it can no longer be used to influence decisions that are still relevant (Zmud, 1978).

In the manufacturing context, the timeliness of information is critical for operational decisions such as production scheduling, inventory management, and response to supply chain disruptions. Research by Negash (2004) shows that real-time BI systems can significantly improve an organization's ability to respond to changing market conditions with more precise and faster decisions. These findings are also in line with the study of Jiang et al. (2002) which emphasized the role of timeliness as a critical dimension of information services.

The Effect of Relevance on the Quality of Decision Making

The relevance of information contributes significantly to the quality of decision-making ($\beta=0.264$, $f^2=0.107$). These findings confirm the importance of personalization and filtering of information in modern driver's licenses in response to the phenomenon of information overload that increasingly threatens managerial effectiveness (Eppler & Mengis, 2004). In the era of Big Data, the ability of SIM to filter and present the information most relevant to the context of a specific decision becomes a crucial competitive differentiator.

A study by Katerattanakul & Siau (1999) shows that relevance is one of the three most important dimensions of information quality for users of web-based information systems, along with accuracy and timeliness. The current research findings confirm the relevance of their findings in the context of manufacturing companies' driver's licenses. From a system design perspective, these findings support the importance of developing customizable dashboard features, user preference-based recommendation systems, and adaptive filtering mechanisms that learn from historical usage patterns.

The Effect of Completeness on the Quality of Decision Making

The completeness of the information had a significant effect on the quality of decision-making (β=0.198, f^2=0.072), although with a smaller effect magnitude than the previous three dimensions. This relatively small influence may reflect the trade-off between completeness and relevance: adding more information to a report does not necessarily improve the quality of decisions if the additional information is irrelevant or creates information overload.

These findings are in line with Miller's (1996) view that completeness has a strong contextual dimension: information that is 'complete' for one decision-maker may be 'redundant' for another, depending on the level of the individual's hierarchy, function, and decision-style. Implicitly, organizations need to develop the concept of 'adaptive completeness' where the system intelligently determines the right level of information detail based on the user profile and the context of the decision.

The Effect of Consistency on the Quality of Decision Making

Information consistency, although it had the smallest influence among the five dimensions (β=0.176, f^2=0.058), still made a statistically significant contribution to the quality of decision-making. The average score of consistency in the 'medium' category (M=3.48) indicates that this is the area that needs the most attention and improvement among the dimensions of information quality studied.

Data inconsistencies are often a symptom of deeper systemic problems, such as lack of standardization of data definitions, imperfect system integration, and the absence of effective master data management (Khatri & Brown, 2010). Madnick et al. (2009) documented how data inconsistencies between integrated systems can be a significant source of decision errors, especially in the context of organizations that rely on data from multiple enterprise systems such as ERP, CRM, and SCM.

Comparative Analysis with Previous Research

Overall, the findings of this study are consistent with and strengthen the existing body of knowledge about the influence of information quality on decision-making. The R^2 = 0.742 value obtained in this study was slightly higher than the study by Gorla et al. (2010) which reported R^2 = 0.68 in a similar context in South Korea, indicating that this study model has better explanatory power, likely due to the addition of a consistency dimension and the use of more refined instruments.

The dominance rating of information quality dimensions (accuracy > timeliness > relevance > completeness > consistency) in this study was similar to that found by Wixom & Todd (2005), although with different coefficients. The difference in coefficient magnitude likely reflects differences in industry context and organizational culture between different research samples. These findings add to cross-cultural evidence about the universality of the importance of accuracy and timeliness as the most critical dimensions of information quality, while also showing contextual variation in the magnitude of the influence of each dimension.

CONCLUSION

This study, using PLS-SEM on 145 respondents from 15 Indonesian manufacturing companies, confirms that information quality in Management Information Systems is generally perceived as high, with accuracy rated strongest ($M = 3.92$) and consistency weakest ($M = 3.48$), indicating ongoing challenges in data integration. All five dimensions—accuracy, completeness, timeliness, relevance, and consistency—have a positive and significant effect on managerial decision-making, collectively explaining a substantial 74.2% of its variance ($R^2 = 0.742$), with accuracy emerging as the most influential factor, followed by timeliness, relevance, completeness, and consistency. These findings highlight the importance of prioritizing data validation, real-time system capabilities, personalized information delivery, and enterprise-wide data governance frameworks to enhance system effectiveness. However, the study is limited by its cross-sectional design, geographic concentration, and reliance on self-reported data. Future research should address these limitations by conducting longitudinal studies across diverse industries and regions, while also examining moderating factors such as decision complexity and digital literacy, and exploring the role of artificial intelligence and machine learning in dynamically improving information quality and decision-making outcomes.

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