Frontiers in Business, Economics and Management
ISSN: 2766-824X | Vol. 25, No. 2, 2026

Analysis of Data Quality and Reliability for AI-assisted Product Decision-Making from the Perspective of Cross-Platform User Analysis

Linhan Peng

School of Computer Science, Faculty of Engineering, The University of Sydney, Sydney, NSW 2006, Australia

Abstract: The user data on different platforms are not uniform and therefore less reliable for AI-assisted product selection. Based on the differences in technical structure, user groups and data-collection methods, this paper examines how problems in data quality spread to the AI decision-making process. User interactions on different devices and browsers are often identified by different IDs. Failure of identity matching results in a loss of data integrity but improves the coverage of integrated da ta. The quality of the data on all platforms is inconsistent; only about half of the respondents have valid system version information in their user agent strings. Data readiness is the connection between AI capability and decision quality, and has an indirect effect of 0.476. There are also errors at the algorithm level. Even if the number of user segments is changed, and the data and algorithm are the same, the gender average deviation will be 54.5%. It can be seen that only by means of data cleaning or model correction is the reliability of decision-making guaranteed. Establish an uninterrupted translation path between business semantics and data semantics, explore how to guarantee the chain of data governance and decision calibration, and focus on studying the function of the calibration mechanism in human-machine collaboration.

Keywords: Cross-platform user analysis; AI-assisted decision-making; Data quality; Data reliability; Product decision-making.

1. Introduction

The quality of product decisions depends on how well we understand the behaviour of users. Currently, the digital behaviour of users is distributed across many platforms, including mobile apps, websites, social media, and smart terminals. Only the data from one platform cover a small portion of the actual circumstances; therefore, cross-platform integration analysis has been carried out. Artificial intelligence has increased the efficiency of analysis, but the actual effectiveness of AI-assisted decision-making is fundamentally constrained by the quality and reliability of the input data. When cross-platform data has incomplete integrity, inconsistent standards or incorrect identity matching, the output of the AI model will deviate from the distribution of real user behaviour and result in a decision error.

The structure of the cross-platform data ecosystem has introduced significantly more complex quality problems compared with the single-platform situation. The collection mechanisms, users of different platforms, and privacy policies are not the same, and thus may lead to systematic bias in model training and application. According to the above research, problems in data quality have reduced the diagnostic ability of these factors and, thus, impaired corporate decision-making. Winter et al. used the CoronaCheck application to determine that there are considerable differences in the reporting of symptoms and infection rates between Android and iOS users, and found an adjusted odds ratio of 2.21 [1]. Conclusions drawn only from the data of a single platform may not apply to users of other platforms. Thus, the technical construction of cross-platform data integration is in fact an engineering system that also needs to address semantic alignment, identity unification, and deviation correction.

At present, studies on data quality focus on data management; research on AI-assisted decision-making focuses on algorithm optimisation. Research that incorporates both the perspectives of cross-platform user analysis is still lacking. The sources of data and the groups of users in a cross-platform environment are different; therefore, there are also data quality issues. Analyze the impact of data quality on the reliability of AI-assisted product decisions in cross-platform user analysis and explore guarantee paths from data governance to decision calibration.

2. Structural Heterogeneity and Quality Degradation of Cross-Platform User Data

The main problem of cross-platform user analysis is the structural disparity of data sources, not a lack of data volume. The different technical structures, users and data collection models of these platforms will inevitably lead to some quality loss during the integration of cross-platform data.

The Data Collection Mechanisms of the Various Platforms are Fundamentally Different. Mobile applications collect behavioural events via SDK embedding; Web pages use cookies and browser fingerprints for tracking; Smart terminals obtain interaction data from device sensors. The Granularity of the collected data and the timeliness of the data may differ. The standardised data from these integrations are available. The Alibaba Cloud Developer Community has shown that the same business behaviour can be triggered by multiple nodes, and the reporting standards of different platforms and versions vary. Inconsistent reporting standards for behaviour-related incidents prevent the construction of reliable BI reports and inhibit the use of growth analysis tools.

Another reason is the user identity mismatch. Identifiers of the same user on different platforms are often different. Cross-device and cross-application identity association use device fingerprints and account mapping. Browser updates,

system patches or randomisation by privacy tools can result in different hash values for the same physical device, and thus the identity is split into multiple independent records. There is another problem with the type of issue in static fingerprint systems: when the signals are too similar, multiple different devices may generate the same fingerprint identifier, and more than one-fifth of device IDs are shared among multiple users. The combination of the two types of failure is likely to reduce identity matching accuracy. Failure to correctly match identities will lead to a fragmented understanding of user exposure and behaviour, and the resulting estimation bias will not just be a loss of data but a systematic error in judgment [2]. For instance, the signal randomisation feature of privacy tools can generate different hash values for the same physical device, thereby fragmenting the identity into multiple independent records. According to Arkose Labs' analysis, more than one-fifth of the device IDs in the static fingerprint system are shared among multiple users. Fragmentation of identity deviation indicates that incorrect identity matching can lead to a fragmented understanding of user exposure and behaviour, causing estimation bias; this is not only a loss of data but also a type of cognitive distortion.

Powala and Slezak have introduced the QEDrants framework to classify data assets according to the two characteristics of data integrity and coverage [3]. Data with high coverage but low integrity is called "Unpolished Diamonds", and data with low integrity and low coverage are referred to as "Hitchhikers". Cross-platform integration improves data coverage, but if identity matching and alignment are not accurate, the integrity of the data may be affected. This tension is the main problem of cross-platform data quality management.

The decline in quality is not sudden. Data quality problems in a single platform can be addressed by the verification mechanism of that platform. However, the quality problems that arise in cross-platform integration are often hidden during data fusion and are difficult to find. Therefore, this is not suitable for the next stage of decision-making.

3. Conduction and Amplification of Data Quality Defects to AI Decision-making

As shown in Section 2, the quality decline of cross-platform integration is both hidden and progressive. The defects will be carried forward in the downstream data processing chain and further aggravated. Propagation can be observed in the training and inference stages of this work.

The basic problem in the training stage is pattern recognition. AI is based on statistical patterns in the training data to build predictions. Systematic biases in the data will lead the model to learn these biases as patterns [4]. When prioritizing the features of software, if the data quality is poor, then the AI's resulting analysis will also be biased. It will, in turn, alter the selection of features and resources and change the release schedule for the product. Even worse, if the AI system continuously receives the same kind of low-quality data, it will gradually become "more accurate" in its predictions; however, this accuracy is actually the result of repeating the amplification of existing biases. Data quality problems will not go away on their own in the AI system; instead, they will be gradually amplified in subsequent iterations. Study of the situation of software function priority showed that when data quality is low, the AI's resulting insights are biased, leading to a series of decisions, such as which functions to prioritize, where to allocate resources, and how to plan the product schedule. If the AI system is repeatedly trained on the same type of low-quality data, the predictions may appear to be more accurate, but in fact, they will continue to have the original errors. The quality problem of the data is not resolved by itself in the AI system; instead, it is compounded each time.

The environment for inference is more convenient to use. The product team uses AI to select functions and adjust the strategy according to the current situation of the input data. If the behaviour of a large number of users cannot be recorded in the data, or if there is an error in identity matching that attributes some users' behaviour to others, then the direction provided by the model will not meet the actual needs of these users. Airfocus interviewed 500 product professionals, and the top reasons for poor data quality and difficulties in data acquisition for AI-assisted decision-making were cited by 32% of them; another 29% believed that the lack of clear use cases and goals was the problem [5].

There is an additional risk of a cross-platform environment. Users of the various operating systems are already different in terms of demographics. If the product team primarily uses data from one platform to train the model and then applies this model to guide cross-platform decisions, they are essentially using the behaviour patterns of a certain group of people to infer the needs of all people. It will not be reported as an "error", but it will be relatively out of date.

The features of the decision-makers will also restrict this effect. People who are more aware of data quality tend to make better decisions. Therefore, although we have provided technical support, we still need to address the problem of how sensitive the decision-making party is to data quality.

4. Dimensions and Identification Logic of Cross-Platform Data Quality Assessment

When data-quality defects reach the decision-making stage, the cost of correction will be very high. Rather than addressing the problems in the downstream process, it is advisable to build an identification and monitoring system at the beginning. Systematic assessment of data quality problems in a cross-platform environment is required at the level of diagnosis and governance.

The six attributes of the six types of information in DAMA-DMBOK are: accuracy, completeness, consistency, timeliness, uniqueness, and validity. However, when used for cross-platform user analysis, the meaning of some dimensions needs to be reconsidered [6]. Consistency refers to the uniformity of the same data in all the records of a specific data source. In a cross-platform environment, we need to consider whether the data of the same user on different platforms are pointing to the same behaviour pattern. The updated edition of DAMA-DMBOK has added "Currency" to the list of quality attributes and further specified the connection between data quality and data integration, metadata management, etc. This way will meet the requirements of cross-platform evaluation.

The new criteria for judging AI's decision-making need to be added. Cross-platform support is also required. It is the ratio of successful cross-platform data association for a single user, and thus indicates the completeness of the user profile. Feature Distribution Stability is also required. If the feature

distribution after cross-platform integration differs significantly from the independent distributions of the individual platforms, then the integration has introduced deviations. Semantic consistency of labels refers to the consistency of the rules for labelling a user across different platforms. Semantic conflict results in the model learning inconsistent classification boundaries.

Evaluation should be an ongoing process of daily operation, not a one-time event. At the collection end, set up quality gateways to flag or block data that does not meet the norms; at the integration stage, establish a consistency verification mechanism to detect conflicts among data sources; at the output end, continuously monitor and track the adoption rate and actual effect of suggestions to form a feedback loop from quality to effect [7].

There are no industry norms at present. There are no standard evaluation criteria for these companies, and thus horizontal comparison and continuous improvement cannot be carried out. As of July 2025, China has issued 42 national standards in the areas of data security and personal information protection, and 18 recommended national standards are under study, including classification and grading, risk assessment, personal information protection, etc. Based on the above, promote the formation of cross-platform data quality assessment standards, set specific definitions, calculation methods and qualified thresholds for key indicators, and raise the data quality awareness of all parties in the industry.

5. The Combined Effect of Platform Bias and Algorithmic Bias

The assessment system will help us find out whether there are problems; then, we can identify the source of these problems. The answer has two parts: half is in the data itself, and the other half results from the accumulation of platform ecosystem and algorithmic bias.

The Effect of Platform Differences on Data Quality Has Been Verified Experimentally. Winter and others analysed the data of 23,063 global users of CoronaCheck and found that Android users reported an average of 2.1 symptoms, while iOS users reported 1.6; the suspected infection rate was 24% for the former and 11% for the latter [1]. After accounting for the factors of age, sex, education and country, there was still a difference; the adjusted odds ratio was 2.21. The editor's comment on this study was: Conclusions based solely on a single operating platform may not apply to users of other platforms. In terms of product selection, if a company has used the data from one platform to train a recommendation model, switching to another platform will significantly reduce the accuracy of predictions, and this problem often goes unnoticed by decision-makers at the time.

Bias in the algorithm is also a type of accumulation. The model needs to be able to process data from all over the place and at various times; there may be some special requirements for the type of data or different display windows. A study by PNAS found that GPT-3.5, GPT-4 and several open-source models systematically preferred AI-generated descriptions in their selection of products, academic papers and film and television content [8]. This "AI-AI bias" refers to the problem where, in the use of AI for cross-platform data analysis and product recommendations, it may implicitly favour information that has already been processed or generated by AI, thereby forming a self-reinforcing loop. If the product team is too dependent on such information, it will no longer consider the original feedback from real users.

The cleaning of data may introduce new fairness problems. According to a study by IEEE Transactions on Knowledge and Data Engineering, over 26,000 model evaluations have been analysed, and it was found that automated data cleaning is unlikely to improve accuracy; in fact, it may reduce fairness if the wrong cleaning technology is selected [9]. When the quality of data relates to gender, race, age, etc., the cleaning operation may inadvertently omit or enlarge the signals of certain groups and introduce new biases into the decision-making process.

Data need to be collected from various places, processed and changed; for instance, normalisation and identification matching are carried out, and at any time, bias may be introduced or enhanced. Bias monitoring and correction need to be conducted at all times during the integration process.

6. From Data Governance to Decision Calibration: A Multi-Layer Path for Ensuring Data Reliability

As errors can occur at any time in the integration process, the data must be reliable at all times. Instead, the whole link from the data layer to the decision-making stage is required. The problem is not a lack of tools; rather, it is the absence of a bridge connecting business language and data language.

A Reference Framework for the Data Layer has been established. ISO/IEC 5259-2:2024 provides a standard model and measurement method for data quality in the analysis and machine learning fields based on ISO/IEC 25012 and ISO 8000, and offers a unified quality discourse system for various platforms and teams [10]. According to the application of the IDG-BI framework, combining constraint verification and drift detection, and combining sensitivity classification with unstructured PII detection can significantly enhance the governance effect; the event detection F1 value reached 0.91, which was higher than 0.78 for pure rule governance and 0.74 for pure statistical monitoring. The focus of governance has moved from post-remediation to early warning.

A Decision-Making Layer for calibration is also required. Research has identified five dimensions for the trust calibration of generative AI: personal use, credibility assessment, trustee definition, agent status, and timing of calibration. Therefore, the output of the AI should be viewed as the object to be continuously verified. Cross-platform data is inherently complex, and it is difficult for decision-makers to intuitively determine the reliability of AI suggestions. Systematic Verification is Required.

Integration of governance architecture is also making progress. A study on the transformation of digital government proposed a four-layer integrated architecture for data collection and sensor layer, governance and verification layer, AI and analysis layer, and application and user layer. All the layers are in a cycle of information consumption and generation. It can help choose a product.

The effectiveness of the governance system depends on whether the translation from business semantics to data semantics can be continuously performed. The "user needs", "functional value" and "experience pain points" of the product decision-making should be transformed into measurable data indicators, and the "completeness", "consistency" and "timeliness" of the data at a certain level also need to be converted into specific meanings of decision-making risks

[11]. The Huawei Cloud Technology Community indicated that when there is no semantic layer to provide a unified semantic context, the results of AI are often unstable. The first function of the semantic layer is to provide a standard-language for the business data. Both directions of the two-way translation must be continuously applied to the decision-making process. At present, most governance systems focus on data-side standardisation and automation, but little attention has been paid to translating business semantics; thus, the transformation of data-quality governance into enhanced decision-making capability has not been fully realized.

7. Conclusion

Cross-platform user analysis has expanded the scope of product decisions, but it has also introduced problems with the quality of data. The combination of technical architecture, user composition and collection logic forms three types of differences; thus, the quality loss in data integration cannot be detected and is accumulated layer by layer. The defects will eventually affect the AI-assisted decision-making process in the following ways: contaminated data input; the model learns that deviations are normal; and thus, the decision systemically deviates. Platform Ecosystem Differences and Algorithmic Bias Add to the Uncertainty. At the same time, the reasons for these deviations are also unclear.

To ensure the reliability of the decision, multiple links must connect data governance with decision calibration. Many advances have been made in the technical-level monitoring and governance system; however, the most difficult problem is not technology itself, but how to continuously translate between business semantics and data semantics, and whether the organisation can form a habit of caution regarding AI output. At present, the most practical choice is to have AI in a supporting role rather than as the decision-making entity, to retain human supervision of the governance and judgment process, and to make verification a regular part of decision-making rather than an occasional correction. Naturally, the range of application for this ruling also needs to be verified experimentally.

The main areas of research in this empirical study are health data, urban governance and software product development. The applications of e-commerce, social media and intelligent hardware have not been fully explored. The applicability of the above results to more large-scale industries has not been verified. Further research can be conducted. What specific patterns of cross-platform data quality defects exist in different industries are not systematically compared at present; whether the process of AI model amplification of bias can be quantified has also not been clearly determined, and how much impact governance intervention can have still requires more robust empirical research for verification. If these problems are not solved, it will be difficult to implement the ideas of cross-platform data quality governance in practice.

References

[1] Winter, M., Probst, T., Keil, T., & Pryss, R. (2025). A comparison of self-reported COVID-19 symptoms between android and iOS CoronaCheck app users. npj Digital Medicine, 8(1), 197.

[2] Lin, T., & Misra, S. (2022). Frontiers: The identity fragmentation bias. Marketing Science, 41(3), 433–440.

[3] Powała, A., & Slezak, D. (2024). QEDrants–Data Quality Quadrants for Business Users and Decision-Makers. In Proceedings of FedCSIS (pp. 79–88).

[4] Sambasivan, N., Kapania, S., Highfill, H., Akrong, D., Paritosh, P., & Aroyo, L. M. (2021, May). "Everyone wants to do the model work, not the data work": Data Cascades in High-Stakes AI. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (pp. 1–15).

[5] Airfocus by Lucid. (2026, May 26). New research: 500 product leaders reveal the biggest blockers to scaling AI. https://airfocus.com/blog/ai-product-management-scaling-blockers/

[6] Alexakis, T., Adamopoulou, E., Peppes, N., Daskalakis, E., & Ntouskas, G. (2025). Evaluating data quality: Comparative insights on standards, methodologies, and modern software tools. Electronics, 14(15), 3038.

[7] Hagn, M., Heinrich, B., Krapf, T., & Schiller, A. (2025). Handling imperfection: A taxonomy for machine learning on data with data quality defects. Decision Support Systems, 196, 114493.

[8] Laurito, W., Davis, B., Grietzer, P., Gavenčiak, T., Böhm, A., & Kulveit, J. (2025). AI–AI bias: Large language models favor communications generated by large language models. Proceedings of the National Academy of Sciences, 122(31), e2415697122.

[9] Guha, S., Khan, F. A., Stoyanovich, J., & Schelter, S. (2024). Automated data cleaning can hurt fairness in machine learning-based decision making. IEEE Transactions on Knowledge and Data Engineering, 36(12), 7368–7379.

[10] Guillen-Aguinaga, M., Aguinaga-Ontoso, E., Guillen-Aguinaga, L., Guillen-Grima, F., & Aguinaga-Ontoso, I. (2025). Data quality in the age of AI: A review of governance, ethics, and the FAIR principles. Data, 10(12), 201.

[11] Rumiantsau, M., & Fokeev, I. (2026). Semantic Layers for Reliable LLM-Powered Data Analytics: A Paired Benchmark of Accuracy and Hallucination Across Three Frontier Models. arXiv preprint arXiv:2604.25149.