Volume 2, Issue 1, 2026, Pages 020–030
| Regular Article | Open Access

Journal of Digital Business and International Marketing

Big Data Marketing Analytics, Technology Quality, and Information Quality in Organizational Performance

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Article Info
Journal of Digital Business and International Marketing
https://www.ansispublications.com/journals/jdbim/jdbim.html

https://doi.org/10.64026/JDBIM/2026003

Received 25 July 2025.
Revised form 18 September 2025.
Accepted 30 September 2025
Available online 05 January 2026.
Published by Ansis Publications.

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Abstract – This paper explores the effects of using marketing analytics systems on organizational and financial performance of various industries. This was done using a structured questionnaire that contained validated constructs and the sample comprised 236 respondents representing the fields of finance, education, manufacturing, and other fields. Measurement model was evaluated in the criteria of reliability, convergent and discriminant validity and then structural model evaluation was done using PLS-SEM. Findings indicate that the quality of technology, quality of information and the level of deployment has a great influence on market and financial performance of an organization which underscores the significance of proper, timely, and integrated analytics systems. Results can be used by practitioners who are interested in improving the data-driven decision making.

Keywords – Marketing Analytics, PLS-SEM, Structural Model, Organizational Performance, Measurement Model, Information Quality, Technology Deployment.

I. INTRODUCTION

Marketing analytics (MA) is a vital element of marketing defined in this study as "the gathering, management, assessment, and reporting of data in data-oriented ecosystem by experts periodically using tools and technologies. They are efficient and effective ways of consolidating big data and generating meaningful information to extract patterns of the market, understand the market, inform decision-making in the market, and improve the pursuit and success of advertisements. This definition attests to a thorough illustration of 'so what', 'how', 'when', 'who', 'where' and 'what' of MA.

Iacobucci et al. [1] used a theoretical review of different definitions of MA. This analysis involved a comparatively new method that is converted into lexical co-occurrence data obtained in the natural language into semantic tendencies in an unsupervised framework. The authors reported about a content-assessment emulator that recreated the process of making a program manually by using statistical methods, machine learning, and algorithms. This evaluation is based on the search process engaged in the first search but goes an extra mile to detect and extract the thesaurus-based concepts in the textual information unrelated to any dictionaries and thus create a conceptual model consisting of related concepts and subject groups. **Fig. 1** displays clustering ideas organized into themes with ideas that have been grouped in the same textual extracts to be close to each other in the conceptual map.

The terms will aid in better analysis of the concept of media and digital change in marketing. Recent research on the topic of digital transformation underlines the generalized method of quality control, with weak innovation and integration in the field. The low-quality of data has a negative impact on strategic, tactical, and operational decisions. In particular, error rates greater than 60% have been seen in industry, and about 30 of them in practice. The inefficient data can lead to misleading the user, thus causing the risk of poor marketing decisions being made. Furthermore, bad data quality hampers such activities like process reengineering in the organization and introduction of business strategies.

An element of the decision-making strategy or process should be included in the best format of presenting information-quality data. During the last several years, much literature on the topic of decision-making has appeared. It has been noted that the correlation between the quality of information (IQ) and decision-making is complicated and thus requires wide research. IQ is a significant predictor of the quality of actions and decisions made by a firm hence, information is seen as being one of the cornerstone organizational resources. In fact, more than 98% of the firm's assets as well as those of its consumers are managed by information and data. A study by Gao et al. [2] confirmed that it is not a major concern in a firm to do things the right way, but to have data that speaks to the right things to do. Experiencing low IQ is viewed as one of the most critical concerns for information consumers for both web-based and casual users, including organizational decision-makers.

Deighton and Kornfeld [3] highlight that poor consumer data costs the U.S. business landscape approximately $610 billion yearly, only on staff overhead, printing, and postage. In addition, the scholars reviewed the business expenses of non-quality data and projected that the costs are approximately 10% to 24% of the net revenue. In another study, Redman [4] posit that without quality data, a firm cannot run and thrive better. Data gathered in organizational processes significantly adds value, but only if it is of high-quality.

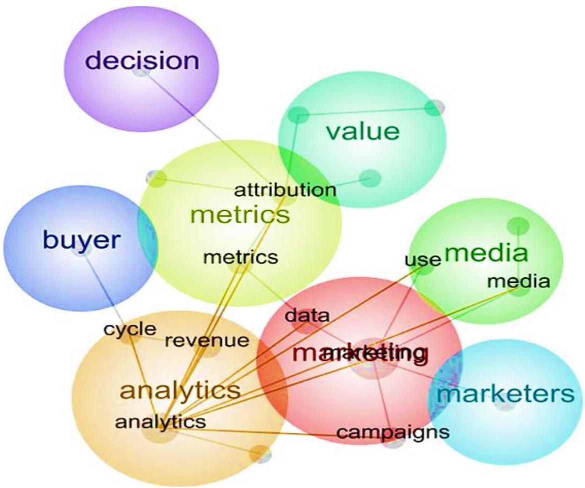

Fig 1. MA Definition Review.

In order to achieve effective application of quality analytics, constructs are established according to the perspectives of industry experts, and these constructs are always subject to approvals. This concept is significant in enhancing our understanding of the issues faced by these experts as well as the industry in the effort to assess organization outcomes and enhance organizational sustainability. In addition, the results provide insights, which can be employed in designing strategies to effectively mitigate these issues, therefore promoting sustainability in Industry 4.0. Insights obtained from MA can help firms to comprehend the issues linked with sustainability and stimulate the establishment of policies, which support Industry 4.0 and sustainable practices.

This paper is aimed at discussing how the deployment of MA affects the performance of an organization. It aims to evaluate the role of technology quality (TQ), information quality (IQ), and level of deployment (LoD), in promoting market and financial performance (FP), by applying a highly developed framework of structural equation modeling, with the reliability and validity testing.

The remaining sections have been organized in the following manner: Section II review related works on data-based marketing analytics as well as business performance. Section III describes our research design and measurement approach, including structural model estimation/predictive analysis. Section IV provides a detailed analysis of our findings, which employed questionnaire with variables for effective data collection. Lastly, Section V concludes our results highlighting the effective application of MA systems to enhance both FP and market of organizations on a larger scale.

II. RELATED WORK

Hitt and Collins [5] suggest a strategic model that can be used by those organizations, which desire efficacy in decision-making. Their research assumes that executives should think, assess, and examine various options. Decision-making is therefore conceptualized as an incremental, systematic process that incorporates the identification, implementation, and selection of alternatives based on a utility function. The authors also argue that successful decision-making entails making the right choice out of numerous choices available; however, this depends on the applicable cognitive abilities, in this case, IQ of the executives or decision makers.

Burke and Litwin [6] observe that executives are able to develop the ability to deal with complex causal models, as well as manipulate them. This possibility is explained by the fact that the metacognitive processes are integrated into the decision-making and allow executives to have cognitive control and produce various alternative decision models with emphasis on the implementation, planning, and interpretation of business purposes. They define information in an organizational context as the information that should be processed. In the absence of tedious processing of such data, firms can be deprived of requisite information to work efficiently. The authors theorize data and information as having similar placements in a spectrum.

According to Karmarkar and Apte [7], there is another definition of information but what is important is that information is not just a documentation or a by-product but a direct result of a process involved in deriving insights into events, objects, places and people which are met in the course of the business operations. When executives have the required information and data, they can make effective decision since information can also be illustrated in form of charts, or tables for easier interpretation. Over the past 5 decades, the literature around marketing has published various advantages of employing MA, such as enhanced decision consistency, review of broader decisions, and ability to evaluate the effects of decision variables. One common these in all is the enhancement of the overall process of making decision.

According to Homburg, Workman, and Jensen [8], rapid environmental and technological changes have changed the content and structure of marketing executives' tasks. These changes integrate (i) an international, hypercompetitive organizational ecosystem, (ii) a rise in management's demand for showing positive ROI (return on investment), (iii) more informed consumers, (iv) using and exploring big data, and (v) universal, networked, and high computing IT architectures. Within this everchanging environments, opportunities for employing MA to enhance profitability should apparently abound. In fact, the whole line of literature mentioned in this section highlights the positive performance effects of applying analytics.

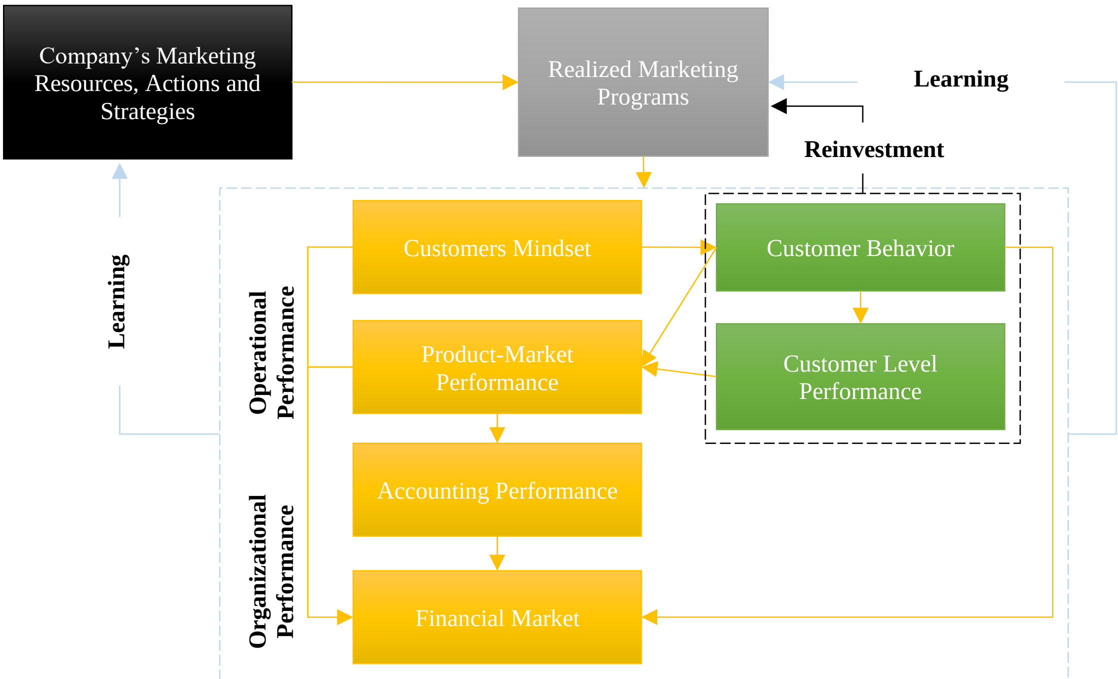

Fig 2. Marketing-Performance Chain and Sample Measures.

Frösén et al. [9] described the general marketing-performance chain illustrated in **Fig. 2** as dynamic in two fundamental constructs. First, businesses reinvest the fiscal resources they produce to maintain and build their market-based capabilities and resources. Second, they also learn by completing different market-performance chain phases in ways that result to changes in their management and selection of future marketing programs and marketing resources. However, Capron and Hulland [10] argues that executives may also transform their organizational resource applications and marketing-based actions in view of the recorded outcomes at any performance chain level, such as fiscal-market outcomes. The scholars agree that it is necessary to redesign literature to enhance our knowledge of the impact of management IT concerning the quality of decisions revolving around easiness, speed, and accuracy of making business decisions. The scholars also reviewed the concepts of managerial information system, which include reliability, relevance, timeliness, and accuracy, to comprehend the concept of IQ

IQ determinants are diverse and vary depending on various environments and systems. Hidayah et al. [11] described the DeLone and McLean Information Systems (D&M IS) Success Model, as illustrated in **Fig. 3**. The model defines IQ as a fundamental element that affects service quality, system quality, user satisfaction, benefits, and overall usage. The implication of conceptual framework of IQ on managerial decisions has been studied by Aydin et al. [12] as illustrated in **Fig. 4**. Moreover, high quality of information is fundamental in attaining the overall benefits, highlighting the significance of timely, complete, and accurate information that will boost user satisfaction and system performance. The scholars also explained the role of IQ on BI (business intelligence) models and how it impacts on governance. In spite of the good connotations that are attached to this concept, Biagi, Patriarca, and Di Gravio [13] indicated that such a concept is still disjointed and that there is still no integrative consideration of the factors that influence it.

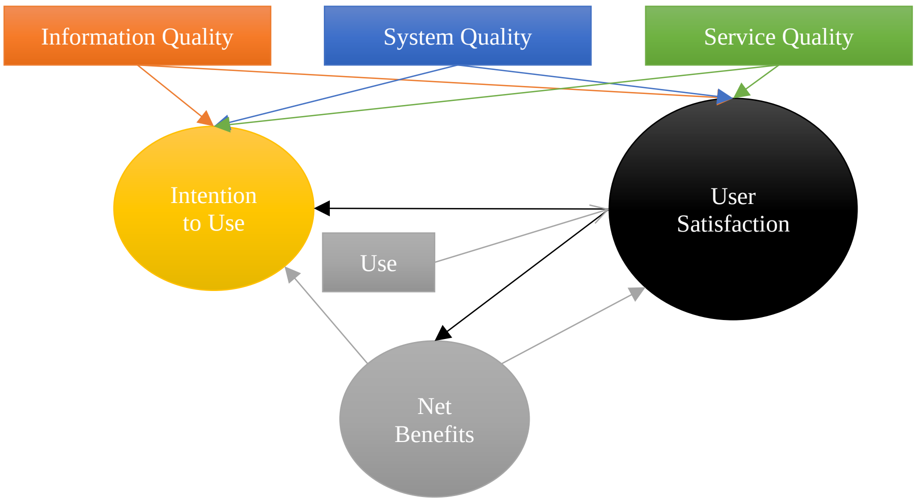

Fig 3. Revised D&M IS Success Model.

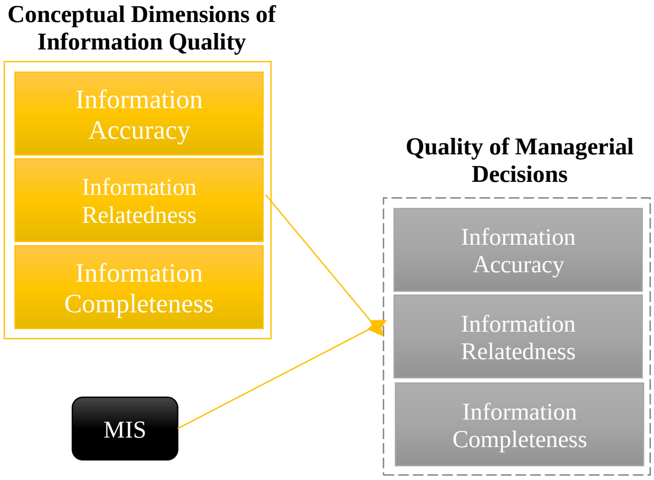

Fig 4. Research Model by Yang et al. [14].

The major elements of QMS (quality management systems) such as enhancing resource effectiveness, addressing system risks, enhancing service/product quality, enhancing stakeholder involvement, and supporting progressive development can aid organizations in attaining sustainable objectives and establish stakeholder value. Li et al. [15] predicted the integration of emerging technologies and analytics-based methods in QMS to complement perennial and traditional practices. DDSQM (data-driven sustainable quality management) operations provide businesses with the ability to assess prevailing issues behind the barriers limiting sustainable quality performance, and to participate in strategic growth. These growth tactics allow the firm to evaluate the level of digital technologies as well as their advantages, which include data access simplicity, and enhancement of data-oriented quality assurance operations.

Lee and Lee [16] acknowledge the significance of big data-informed MA, and encourage firms to continue enhancing their ability to evaluate information and data, and utilize contemporary technology to boost their organizational operations and processes.

III. DATA AND METHODS

Research design and measurement

The research design is a quantitative and cross-sectional study which employs structure equation modeling based on variance to test the hypothesis that MA deployment is related to organizational performance mediated through technology and IQ mechanisms. The paradigm of the methodology is a predictive modeling model, which emphasizes explaining the variance in endogenous constructs rather than seeks the best model fit. **Fig. 5** demonstrates the general research design as well as the step-by-step decision-making process, which begins with specification of theoretical constructs and continues with the development of measurement instruments, data collection, and finally the model estimation procedures that ensures the logical distinction between scale validation and hypothesis testing is strictly adhered to [17].

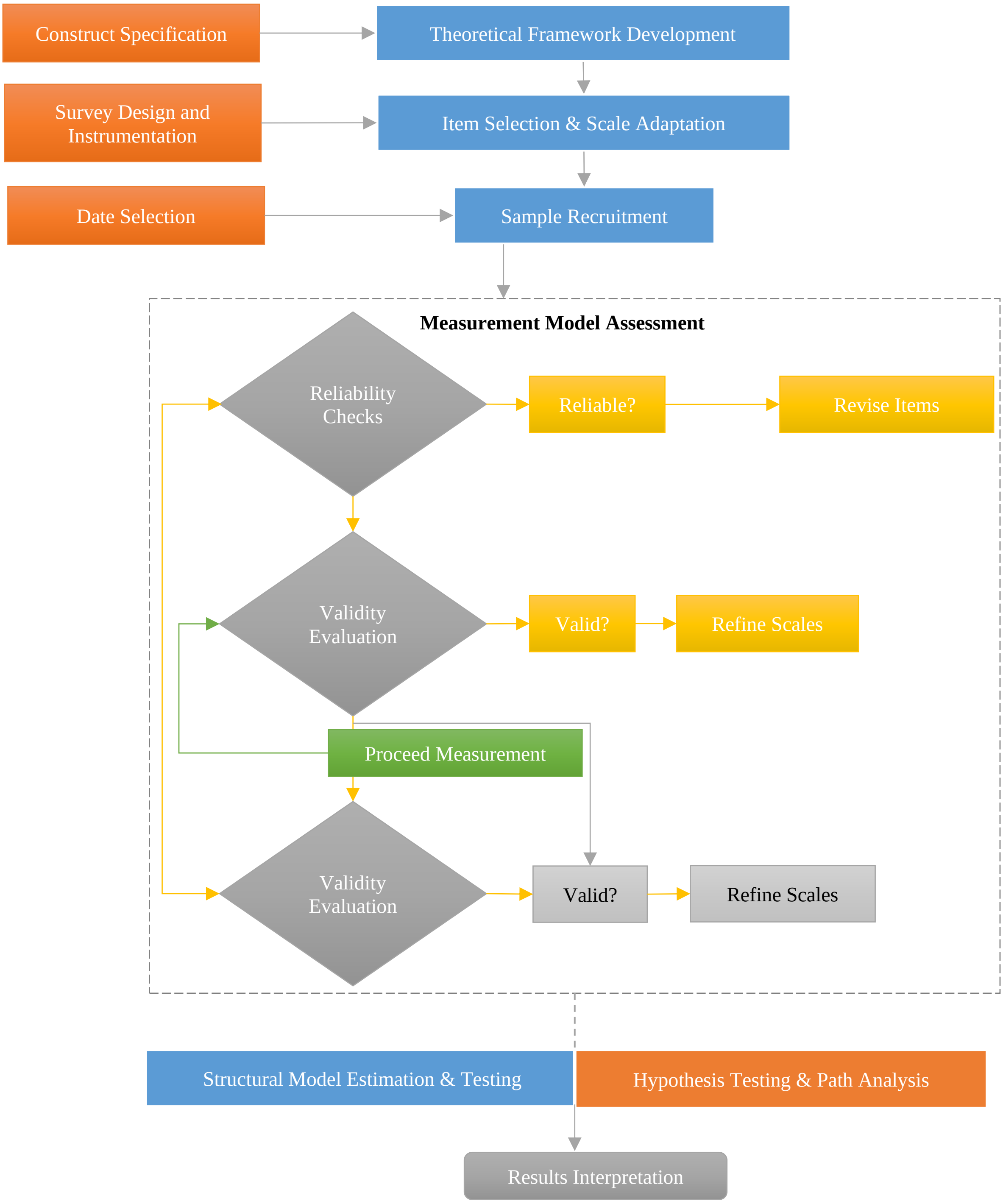

Fig 5. Research Design and Decision Flow of Analysis.

The design of the measurement instrument was based on the systematic adaptation of validated scales from previous MA and information systems literature so that the construct validity and theoretical continuity can be established. All latent constructs were modeled in a reflective way, consistent with the assumption that recorded metrics are indicators of any prevailing conceptual variables. The application of the five-point Likert feedback format was chosen to balance the need for sensitivity in the scale with the need for reliability of respondents as well as comparability across constructs.

Measurement quality was explored through a series of reliability and validity analyses integrated into the analytical plan demonstrated in **Fig. 6** that illustrates the measurement model decision flow. Indicator reliability was examined using standardized outer loadings, which is the squared loading representing the percentage of measurement error variance, which is defined by latent variables in Eq. (1).

Fig 6. Evaluation Model for Measurement Decision Flow.

$$IR_i = \lambda_i^2 \tag{1}$$

where λ_i denotes the standardized loading of indicator i. Internal consistency dependability was determined based on both Cronbach's alpha and composite reliability in order to establish the lower and upper bounds of construct reliability. Cronbach's alpha is given using Eq. (2).

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_i^2}{\sigma_T^2}\right) \tag{2}$$

where k is quantity of indicators, σ_i^2 represents the variance of indicator i and σ_T^2 the overall construct variance. Composite reliability was calculated in consideration of unequal indicator loadings in Eq. (3).

$$CR = \frac{\Sigma \lambda_i)^2}{(\Sigma \lambda_i)^2 + \Sigma \theta_i} \tag{3}$$

where $\theta_i = 1 - \lambda_i^2$ is the indicator error variance.

Convergent validity has been assessed by using AVE (average variance extracted) that determines the quantity of variance detailed by constructs rather than by measurement error in Eq. (4).

$$AVE = \frac{\sum_{i=1}^{k} \lambda_i^2}{k} \tag{4}$$

To improve methodological transparency, **Table 1** presents numerical design thresholds used in the evaluation of measurement models, rather than empirical results, so that the measure does not duplicate the results section.

Table 1. Numerical Thresholds Used in Measurement Model Evaluation

Metric	Symbol	Minimum Threshold	Upper/Reference Bound
Indicator reliability	λ^2	0.50	—
Cronbach's alpha	α	0.70	0.95
Composite reliability	CR	0.70	0.95
Average variance extracted	AVE	0.50	—
HTMT ratio	HTMT	—	0.90

Discriminant validity was measured in terms of Heterotrait- Monotrait ratio, and is calculated as the ratio of the between inter-construct relationships to within construct relationships computed using Eq. (5).

$$HTMT_{ab} = \frac{\frac{1}{n_{ab}}\sum|r_{ij}|}{\sqrt{\frac{1}{n_{aa}}\sum|r_{ii}| \cdot \frac{1}{n_{bb}}\sum|r_{jj}|}} \tag{5}$$

Bootstrapped confidence intervals were used to test the statistical distinctness of HTMT values from unity, per recommendations for using higher order models with repeated indicators.

Structural Model Estimation/Predictive/Effect Analysis

The structural model estimation phase offers an assessment of hypothesized relationships between analytics deployment, quality of technology, quality of information, and performance of the organization. **Fig. 7** shows the structural model decision flow describing collinearity diagnostics, examination of predictive validity and hypothesis testing logic. Prior to the estimation of the path, the collinearity between the exogenous constructs was analyzed, using the Variance Inflation Factor in Eq. (6).

$$VIF_j = \frac{1}{1-R_j^2} \tag{6}$$

where R_j^2 refers to the constants of determination in predictor j regression on all other potential predictors in the model. VIF values less than conservative values are an indicator that parameter estimates are not biased by multicollinearity. Predictive validity was evaluated by using the coefficient of determination (R^2) as well as Stone-Geisser's predictive relevance statistic (Q^2) as obtained by blindfolding. The R^2 statistic is expressed in Eq. (7).

$$R^2 = 1 - \frac{\sum(y_i-\hat{y}_i)^2}{\sum(y_i-\bar{y})^2} \tag{7}$$

while predictive relevance is calculated using Eq. (8).

$$Q^2 = 1 - \frac{PRESS}{SSO} \tag{8}$$

where $PRESS$ is the prediction error sum of squares and SSO the sum of squares of observations. Positive Q^2 values are a sign that the model has out of sample predictive capability for the endogenous construct.

Hypothesis testing was performed by nonparametric bootstrapping which produces empirical sampling distributions of path coefficients without assuming normality. Path significance was taken in conjunction with effect sizes to determine substantive impact. Effect size (f^2) was computed using Eq. (9).

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1-R^2_{included}} \tag{9}$$

This measure relates the relative contribution of each of the exogenous constructs to the explained variance for the endogenous variable and is independent of sample size making comparisons between studies easier. To further create robust support for the model, the value of path coefficients was standardized by interpreting the sum of direct and indirect effects across mediating constructs (i.e. standardized total effects) in Eq. (10).

$$TE_{xy} = \beta_{xy} + \sum(\beta_{xm} \cdot \beta_{my}) \tag{10}$$

This formulation is useful in achieving an elegant understanding of the process of MA deployment and its effects on the outcomes of performance, including the direct and indirect effects through quality-related mechanisms.

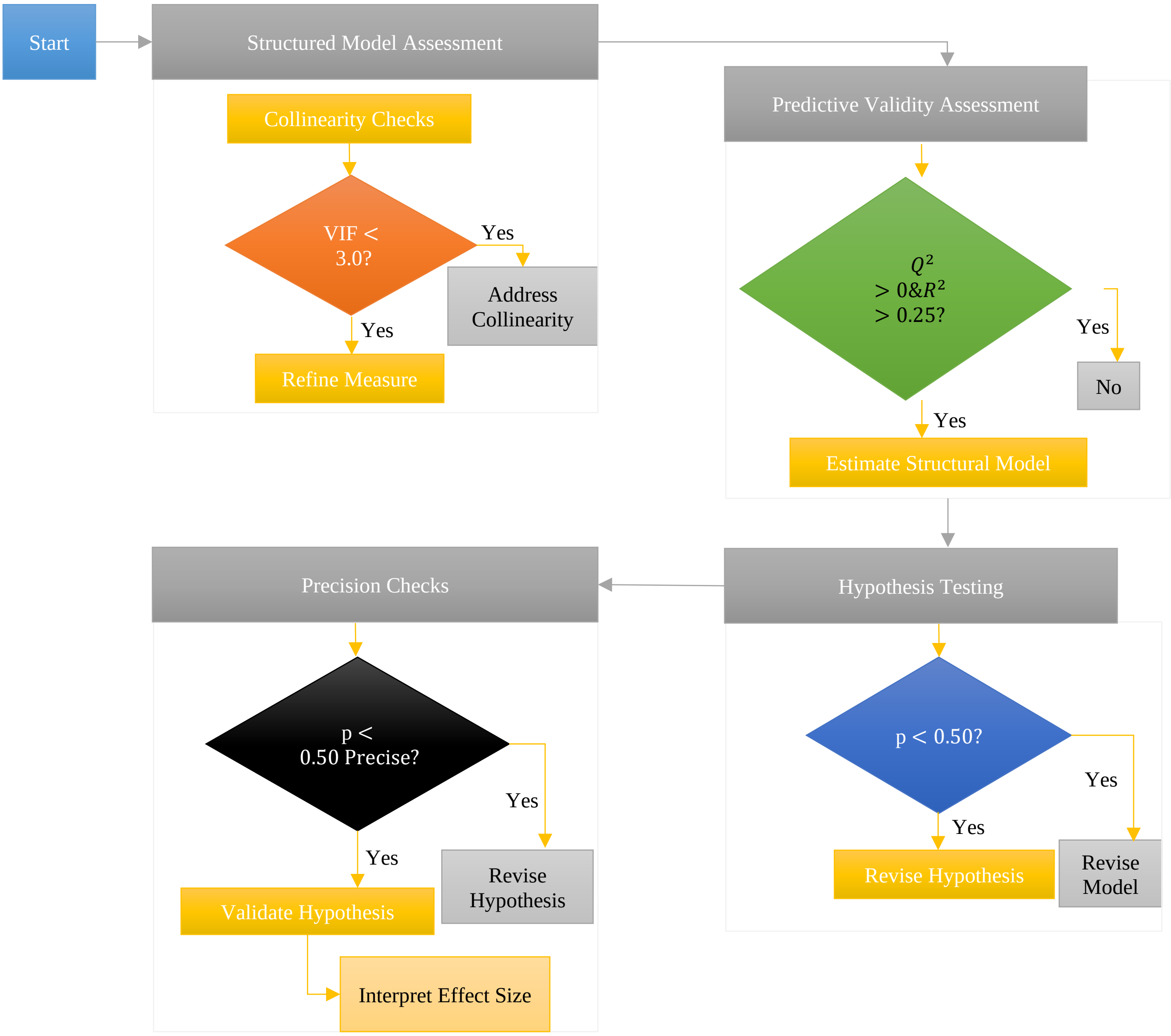

Fig 7. Decision Flow of Estimation and Hypothesis Testing of the Structural Model.

IV. ANALYSIS OF RESULTS

An instrument that included variables derived in reference [18] was designed and then used to collect the data through administering a questionnaire (see **Table 2**). The tool lays an emphasis on the constructs and the variables that are attached to them. Moreover, the entire items were applied on a five-point Likert scale where 1 meant ‘strongly disagree’ and 5 ‘strongly agree’; this scale was used in all queries except deployment level. **Fig. 8** highlights the population of the study sample ($n = 36$). Participants were obtained from different types of industries, such as insurance and finance; real estate, construction, manufacturing, educational services, cultural and information industries.

Our initial phase assessed the different scales employed to calculated different constructs. The process began with the evaluation of indicator reliability (IR). An accelerated and bias-rectified bootstrapping assessment was done to determine the relevance of indicator variables. All factor loadings were more than 0.7, which implies that the relation between indicators and their respective constructs was significant.

The second phase assessed internal consistency reliability (ICR), as described in **Table 3**. Agbo [19] highlighted that Cronbach’s alpha provides a conservative reliability measure to determine ICR. The reliability target between 0.7 and 0.95 will probably increase ICR. In that regard, the actual reliability lies between the two measures. The lower and upper limits are the Cronbachs alpha and Intra-class Correlation Ratio (ICR), respectively. In this regard therefore, the ICR is considered adequate. As far as convergent validity is concerned, which is determined by the Average Variance Extracted (AVE), 0.5 is the lowest possible value.

The third phase is the evaluation of discriminant validity (DV) that represents the range to which constructs vary from other distinct constructs. Standard procedures cannot be used to achieve this, especially for high-order models because of the deployment of repetitive indicators. Existing studies show that high-order elements only require assessment as an element of structural modeling of DV.

We support the application of HTMT (Heterotrait-Monotrait) of correlations, which represents the between-trait correlation ratio to within-trait ones. However, a 0.9 threshold value should not be more than the values of HTMT correlation. A test to determine significance level should be done since HTMT evaluation acts as a benchmark for DV tests. Standardized tests cannot be employed to evaluate whether HTMT correlations are meaningfully distinct from values of 1, as the usage of PLS-SEM does not integrate distribution hypotheses.

Therefore, bootstrapping processes have been proposed to test significance level. Bootstrapping confidence intervals, which integrate the value of 1 will show a deficiency of DV. No confidence interval integrates this value, which shows that DV has been attained (irrespective of the fact that one of the HTMT values exceeded the 0.9 threshold). A collinearity analysis was part of the assessment of the structural model, which helps to demonstrate the correlations between exogenous predictors, and was logically analyzed through the variance inflation factor (VIF). The entire values of VIF were less than the predetermined 3, therefore, showing the lack of significant collinearity between the predictors.

Table 2. Study Variables and Constructs

Constructs	Description
LoD	This shows the degree of familiarity, appraisal, acceptance, and extensive application of MA applications in the key processes of the organization.
Performance	Measures the capability of the organization to gain quicker access into the market, launch new products or services quicker, gain success more frequently and gain market share as compared to their competitors.
FP	This is an outcome measure that includes customer retention, sales growth, profitability, and an outcome on return of investment as a result of MA usage.
Format	Defined as the extent to which information generated by MA is well organized, simple to comprehend and clearly given to the intended users.
Accuracy	Shows the accuracy and precision of information produced by MA systems.
Currency	Gauges the degree to which MA systems offer the latest and the most current information.
Completeness	Shows whether MA systems provide complete and adequate information to make decisions.
System Privacy	Defines the capability of the system to safeguard individual and sensitive information and guarantee the confidentiality of data.
System Integration	The ability to engage and integrate information of several sources of data of an organization into a single perspective is reflected.
System Adaptability	References the elasticity of the MA system with regards to adapting to evolving demands and new analytical demands.
System Reliability	Determines the consistency and reliability of the MA system in aiding the analytical operations.

Table 3. Predictive Strength and Significance

Constructs	Q^2	R^2 Adjusted	R^2
TQ	0.02	0.02	0.03
MP	0.63	0.64	0.64
IQ	0.05	0.05	0.05
FP	0.60	0.61	0.61

Table 4. Significance Of Path Coefficients in the Overall Model of the Dataset

#	Exogenous constructs	Impact size definition	Impact size (f)	Hypothesis support	p-values	Path coefficients
1	TQ -> MP	Medium to small	0.11	Yes	0.001	0.47
2	TQ -> FP	Medium to small	0.08	Yes	0.000	0.43
3	LoD -> TQ	Small	0.03	Yes	0.015	0.16
4	LoD -> IQ	Medium to small	0.05	Yes	0.000	0.22
5	IQ -> MP	Medium to small	0.06	Yes	0.006	0.35
6	IQ -> FP	Medium to small	0.06	Yes	0.001	0.37

The final phase focuses on an analysis of path coefficients and its significance within the structural framework. This phase is similar to hypothesis testing, as computed in **Table 4**. Existing research by Peeters [20] show that statistical relevance is not sufficient when documenting research findings. This is why it is also justified to document the effect size. The most important criterion of quantitative evaluation may be effect size.

When using a very large sample the statistical testing technique can be used to establish significant differences that will lead to one, practically useful interpretation especially in large scale, data-driven marketing cohorts. This means that p-values reporting is not sufficient. The results of our empirical analysis show that, 0.35, 0.15 and 0.02 are values of exogenous constructs that have large, medium and small effects, respectively. Impact size is not impacted by the size of samples, which shows that it can be compared between various literature works.

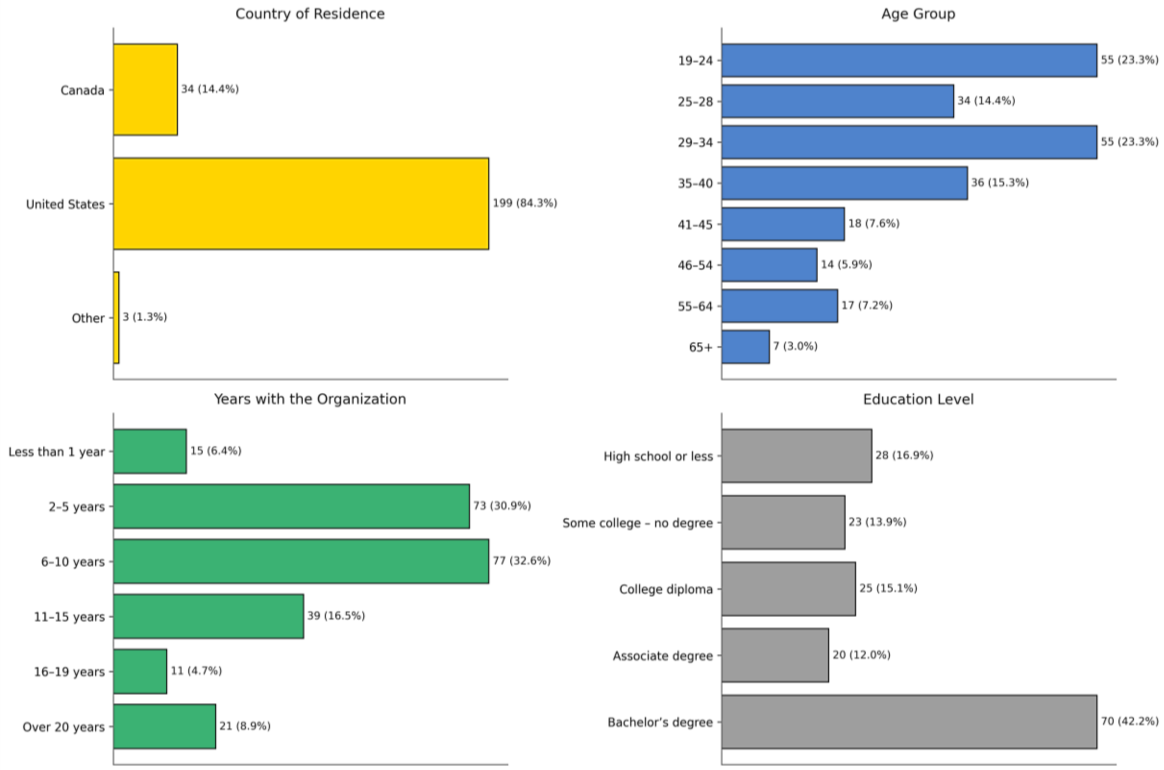

Fig 8. Sample Description.

V. CONCLUSION

The results of this study show that the effective deployment of MA systems improves both market and FP of organizations to a large extent. TQ and IQ became the driving forces, highlighting the need for accurate and timely information that is well-integrated in order to make decisions. The structural model analysis established that increased levels of deployment have positive effects on performance outcomes, which makes this finding relevant to managers who want to find a way to optimize their analytics capabilities. Moreover, the measurement model validation ensured that constructs were reliable and distinct to strengthen the credibility of the results. By correlating the nature of analytics systems with measurable business outcomes, this research delivers evidence-based advice for organizations seeking to adopt data-driven ways of working to deliver competitive advantage.

CRediT Author Statement

The authors confirm contribution to the paper as follows:
Conceptualization: Anandakumar Haldorai, **Methodology:** Amelia James, **Software:** Anandakumar Haldorai and Amelia James, **Data Curation:** Anandakumar Haldorai and Amelia James, **Writing- Original Draft Preparation:** Anandakumar Haldorai and Amelia James, **Visualization:** Amelia James, **Investigation:** Anandakumar Haldorai, **Supervision:** Anandakumar Haldorai, **Writing- Reviewing and Editing:** Anandakumar Haldorai and Amelia James
All authors reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

No funding agency is associated with this research.

Competing Interests
There are no competing interests.

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ISSN: 3104-4115