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Research article

Valuation of big data analytics quality and competitive advantage with strategic alignment model: from Greek philosophy to contemporary conceptualization

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Abstract: Around 333BC, Diogenes Laertius cited (Greek quote): "οὐκ ἐν τῷ μεγάλῳ τὸ εὖ…, ἀλλ' ἐν τῷ εὖ τὸ μέγα", which means that volume (big data: tera, peta, velocity and variety) doesn't guarantee quality. Furthermore, Protagoras's doctrine about homo mensura and the Socratic Maieutic method evidences demonstrated the way that queries (SQL) on big data can play on specific needs when crafted, such as turning big data into knowledge and a competitive advantage. In this research, an alternative to the data-driven approach will be propounded with the development of the strategic alignment model (SAM) based on the principles of Greek philosophy. The SAM model will support decisions of big data analytics structure with strategies to fit and align in a way to create a competitive advantage. Mathematical formulation of the model will help to optimize a competitive advantage through the economic value added (EVA) to guide the proper strategy and big data analytics structure in a holistic framework. Conclusions will be drawn on how strategy and the structure of big data analytics can be aligned.

Keywords: big data analytics; strategic alignment model; competitive advantage; greek philosophy; Plato; socratic maieutic; economic value added (EVA); optimization; strategy; structure

JEL Codes: G10, G11, L15, M15, M20, N00

Abbreviations: BDA: Big data analytics; CA: competitive advantage; SAF: strategic alignment framework; SAM: strategic alignment model; SA: strategic alignment; EVA: economic value added; ROIC: return on capital; WACC: weighted average cost of capital; NOPAT: net operating profit after tax; EBIT: earnings before interest and tax; IT: information technology

1. Introduction

As cited by Athenaeus[1] and Diogenes[2], a famous ancient Greek quote of Caphisius says the following: "οὐκ ἐν τῷ μεγάλῳ τὸ εὖ…, ἀλλ᾽ ἐν τῷ εὖ τὸ μέγα", which means that volume (quantity no matter how big, mega, giga, tera, peta…) doesn't guarantee quality (big like mega ~«μεγάλῳ»). The same holds for big data analytics (BDA), as quality might be within big data, though big data doesn't always guarantee quality. Paraphrasing Poincare's famous quote about science: "Knowledge buildup of data as a house of stones but a collection of data (no matter how big in volume, velocity and variety), is no more knowledge than a hip of stones is a house". Otherwise stated, quality might not be within the average or the central 90% of data distribution; for example, 70% of twitter messages come from only 2.5 % of users, and the highest percentages of revenues (for many businesses) comes from the lower part of products and customers. Just as the German proverb says, "Der liebe Gott steckt im detail", whose paraphrasing means distributions tails refer to personalization and customization instead of the mean (average) of the distribution (center). As cited around 368 BC in one of Plato's dialogues Theaetetus[3] (about the earlier teaching of Protagoras): "πάντων χρημάτων μέτρον ἐστίν ἄνθρωπος", which means that the best and optimal metric system is each one's individual's opinion, each opinion is valuable, homo mensura. In the above-mentioned dialogue, Socrates refers to Protagoras thesis of an individual's perceptions: person's realities and truths are of higher value compared to the consensus, thus raising the value of a customized, customer centric, niche strategy or customer centric approach. It is worth mentioning that a consensus is what is known, either to us or to others, while a higher contribution (of data analytics) might be the capability to determine the unknown unknowns. Summarizing this point, the significance of setting appropriate queries must be crafted to individual needs.

In order to guarantee quality it is significance, not only the content of the question itself, but the ability to set the questions (i.e., queries) in a way that provides the best guidance to optimal decision making. Thus, beyond the tools we use, a framework is needed to set correct questions (i.e., queries). Tools alone (structured query language (SQL), extensible markup language (XML), really simple syndication (RSS), artificial intelligence (AI), machine learning (ML), etc…) cannot improve nor enhance our ability to set queries (i.e., questions) that increase competitive advantage (CA). As Roger Penrose said, "… algorithms, in themselves, never ascertain truth! It would be as easy to make an algorithm produce nothing but falsehoods as it would be to make it produce truth. One need external insights in order to decide the validity…" (Emperor's New Mind, 1989). Thus, as set in Google's 6-

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[1] Athenaeus of Naucratis, 3rd-century AD, Deipnosophistae, book 14, 629a-b, https://en.wikipedia.org/wiki/Deipnosophistae.

[2] Laërtius Diogenes, 3rd-century AD, Book VII, (about life of) Zeno 21, https://en.wikisource.org/wiki/Lives_of_the_Eminent_Philosophers/Book_VII.

[3] Plato, dialogue Theaetetus, 369 BC, section 152 a, https://www.perseus.tufts.edu/hopper/text?doc=Perseus%3Atext%3A1999.01.0171%3Atext%3DTheaet.%3Asection%3D152a

step process of professional data analytics certification, the first and most important step is to “ask” (question), while the other steps include preparation, processing, analysis, sharing, and act. From Plato’s texts about Socratic dialogues, we know that since 399–387 BC, great value was given to the questioning as queries form the basis upon which the developed Socratic Maieutic method[4], since knowledge was believed to exist as a memory derived by the correctly guided queries (Plato, Socratic inductive reasoning Vs Aristoteles deductive reasoning). According to K. Pooper in inductive reasoning, big data (i.e., observations) triggers a serial pattern from hypotheses to theory, while in deductive reasoning, theory triggers hypotheses and big data (i.e., observations) that are subsequently used for validation and confirmation.

It’s essential to determine quality in the above-mentioned six-step process of Google’s big data analytics, which must be customer centric (crafted on specific individual needs). Research of the last five years has indicated that big data analytics strategic alignment still occupies literature, though its contents were examined independently and lacked a coherent framework to study interactions/correlations and their effect on performance. The innovative aspect of this research was the development of a coherent framework at the BDA managerial level to ensure that queries (i.e., questions) were appropriate to guide decisions and knowledge towards CA. Big data is just the available means to transform data to knowledge, similar to a hip of stones to a house, though we need an “end” to justify the “means”, “Exitus acta probat”[5]. n this model, the CA criterion (through an economic value-added approximation) will be used as the “end”, which will “reveal” not only the “known knowns” and the “known unknows”, but also provide the basis to derive the “unknown unknowns”[6]. The whole process will guide management and decision making for setting the appropriate queries by the maximization of an economic value-added function (EVA). Quality will be guaranteed by the appropriate queries, as derived by the strategic alignment framework (SAF), which will guide the whole process of data analytics to obtain the optimum strategic decisions. The analysis feed of big data can be derived not only from the historical data, but also from an advance in the time data frame (through derivative markets, options, forward, and futures) kept in either internal or external DBASE systems (Theodorou & Karyampas, 2007), which might help to uncover part of the unknown unknowns.

The following literature review section will present a discussion on big data analytics and strategic alignments. In the model paragraph thereafter, a strategic alignment model will be presented along with its elements and mathematically formalized interactions to achieve a maximal economic value. Finally, conclusions will be drawn on how strategy and the structure of big data analytics can be aligned in a way to create a competitive advantage.

2. Literature review

The environment of the ‘80s is characterized by a demand for qualitative diversification and the development of market niches, which both forced a production model to turn around from mass

[4]Dell recognized the connection among Big Data Analytics and Socratic Method since 2014 (Bartik 2014)

[5] Epistulae Heroidum, 5 BCE, Phyllis to Demophoon, Pūblius Ovidius, line 85 of Heroides II, https://en.wikipedia.org/wiki/Ovid, https://en.wikipedia.org/wiki/Phyllis(mythology), http://www.perseus.tufts.edu/hopper/text?doc=Perseus%3Atext%3A1999.02.0085%3Apoem%3D2.

[6] Press Conference by US Secretary of Defence, Ronald Rumshfeld, 6 June 2022, NATO HQ, Brussels, https://www.nato.int/docu/speech/2002/s020606g.htm.

production to market niche customization on specific individual needs though a lean and flexible production (Theodorou, 1996). Costs gave ground to the strategies of innovation, quality, flexibility, and dependability through product customization, while advancements of information technology during the ‘90s (Vlachopoulou et al., 1994; Manthou et al., 1996) permitted production flexibility and the customization of goods on individual needs (homo mensura). A key ingredient of success is information technology, in which big data analytics along with AI plays a key and central role. These developments have previously been pointed out by Theodorou (1994, 1996, 2005). The economic characteristics of mass production, including hard automation, just-in-case systems, scale economies, cost strategies, and vertical integration, gave ground to just-in-time systems, flexibility, scope economies, diversification, outsourcing, and lean production. After the 00’s, a new production model, namely ‘Commons Based Peer Production’ (Benkler, 2002), was characterized by recycling, environmental and social sustainability, and (most importantly) sharing access on assets, in which data warehouses moved to ‘cloud computing’ structured in an ‘everything as a service’ (IaaS, PaaS or SaaS) and a ‘pay as you go’ model. The consumer’s role now mixed prosumer and product customization (i.e., tailored production), which was achieved through customerization. Flexibility, along with customerization, is based on Protagoras’ perception about homo mensura. In this model, the growth of data (volume, velocity, value, variety, and veracity) lead to a knowledge-based and team learning organizational structure that is based on business intelligence. Customerization requires an exchange of information and knowledge between the customer and producer on an ongoing basis.

Those developments incentivized Theodorou to develop the strategic alignment model (SAM) (Theodorou, 2003; 1996; 1996a; 2004) based on the management of the research framework of Morton (1991). The discussion on the strategic alignment (SA) concept is mostly found in the strategy and organization theory, which constitutes the groundwork of strategic information systems. The SA concept literally refers to a relational arrangement of forces, since correlation is a core concept in big data analytics. Those forces are as follows: the environment (regulatory, competitive, and physical) where the organization operates, the structure, the technology of big data analytics, and the organizations’ strategy (Figure 1). Around the mid ‘80s, the business strategy and economic environment were perceived as the main forces of the alignment process, while the structure was conceived as an internal arrangement within which the big data analytics’ role was collateral (Miles & Snow 1984). Alterations in the economic model happened in mid ‘90s, of which the most important concepts to name are uncertainty and flexibility (Theodorou, 1996a), which changed the conceptualization to a bottom-up view (Mintzberg & Quinn, 1996), where alignment forces were interrelated in a multidimensional way (Theodorou, 2000). The increased need for flexibility raised the importance of big data analytics whose effect on structure (by enhancing the structural elements of flexibility and “craftability”) decreased variability and uncertainty, with a final positive impact on the CA. However, except of operational benefits, the CA cannot be gained if the fit among the BDA and structure is not aligned with strategic targets. The BDA must support and interact with a business strategy. Such alignment must be achieved throughout all levels and perspectives: strategy execution, technology, and competitive potential. BDA and business strategy alignments were extensively examined in the ‘80s by Porter (1979, 1987) and in the ‘90s by Neumann (1994) and Wiseman (1998). Extensive literature analyses and presentations of most of models can be found in Theodorou (2003), where the strategic priorities of cost, quality, flexibility, dependability, innovation, and customer service were determined in detail (see the undermentioned paragraph: “Strategic Alignment Model on BDA”).

After an extensive big data analytics literature review (more than 5000 articles in Scopus and 3000 articles in Web of Science between 2010–2018, of which 185 papers were examined and refined to 25), Shdifat et al. (2019) concluded that most studies failed to grasp the capabilities of big data analytics to create a CA while performing a sheer epidermal system examination. Exceptions to that conclusion include the studies of Gupta and George (2016), Wamba et al. (2015), Akter et al. (2016), Grover et al. (2018), Wang et al. (2016), and McAfee et al. (2012), which all recognize the capability of big data analytics to conditionally create a CA upon the restructuring of business processes (such as to address the rapidly changing environment). In this analysis, the empirical research prevails (of the decade literature), with the larger part (84%) identifying and validating relationship models applying structural equation modelling, thus closing an important gap in business practices and the application of the strategic alignment model.

An organization theorists' approach, structure, and BDA relation utilizes contingency models such as the SAM. Structural enhancements can be achieved by a lean and flexible character, taking advantage of the BDA capabilities in a way to accomplish the uncertainties and crafted needs that the competitive environment requires. The examined concepts of SA are as follows: moderation, mediation, matching, covariation, deviation, and gestalt, along with their structural dimensions and variables (modeling paragraph: "Strategic Alignment Model on BDA"). The strategic alignment concept of moderation and matching confirm the performance implications (Bergeron et al., 2001). Theodorou (2001) concluded that structural alignment attained by decentralization and low formalization enabled matrix structure and strategic flexibility contingent on the environmental uncertainty and business size. Those were the main structural characteristics of a knowledge-based learning organization, adhocratic with a shared vision, personal mastery, and team learning with a diversified product portfolio.

At this point it's interesting to notice that 26 years after the initial development of SAF, in "The age of Analytics: Competing in a data driven world" report[7] (McKinsey, 2016), McKinsey raised the gap due to an absence of a strategic alignment framework: "…The first challenge is incorporating data and analytics into a core strategic vision. The next step is developing the right business processes and building capabilities, including both data infrastructure and talent. It is not enough simply to layer powerful technology systems on top of existing business operations. All these aspects of transformation need to come together to realize the full potential of data and analytics. The challenges incumbents face in pulling this off are precisely why much of the value we highlighted in 2011 is still unclaimed."

The subject of big data analytics strategic alignment still occupies literature. However, most studies separately examined the various aspects of SA and were not examined in a coherent framework. Some studies approached the strategic perspective (Pesce & Neirotti, 2023; Ngo, 2023; Smith & Thomas, 2023; Martinsuo & Anttila, 2022; Karlsson et al., 2023), others tried to encompass the advances of information technology and the effect of big data analytics (Chen et al., 2022; Pelletier & Raymond, 2023; Lei et al., 2023; Primasari, 2022; Akter et al., 2016), while a few focused on the structural aspects (Wang et al., 2023; Pashutan et al., 2022; Arshad et al., 2023). It can be noted that literature still lacks a coherent approach, such as the one proposed.

[7] https://www.mckinsey.com/business-functions/quantumblack/our-insights/the-age-of-analytics-competing-in-a-data-driven-world

3. The strategic alignment model on BDA

Our thesis is that BDA's technology (per se) is not a necessary and sufficient condition for the increase of corporate performance. The SAM generates a CA (Theodorou, 2003, 2008; Theodorou & Dranidis, 2001). As pointed out in the literature discussion, the BDA technology must be guided from a SA valuation framework (SAF) in a way to provide a CA through the fit of a BDA with structure (i.e., Equations 4–6) and the alignment with strategy and the environment (Equation 1: physical, regulatory, and market competitive). Market niches and demand variability necessitate the flexibility in corporate structure to accomplish product customization and variety. Moreover, important tradeoffs among strategies, such as cost vs innovation, cost vs quality, etc, need continuous adaptation of structure and the BDA (Equation 3). This process needs a decision support model such as the SAM and continuous monitoring and adaptation (Figure 1, Theodorou, 2003).

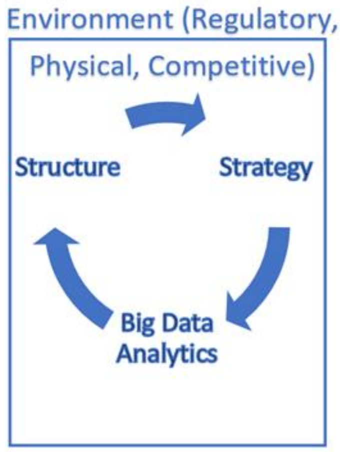

Figure 1. Matching: ((struct<->BDA<->strat)->CA
Mediation: (strat->BDA->struct->CA)
Moderation: (BDA->strat->(struct->CA))

For example, the attainment of the "just-in-time" strategic target creates trade-offs among increased inventories (increased security) and increased costs (of capex and opex), as well as increased financial risks (due to value, price fluctuation of commodities kept in depositories). A CA is financially estimated with the EVA and the return on invested capital (ROIC) (Theodorou & Florou 2008). As described in the matching perspective, the interaction effects play a significant role in achieving a beneficial performance and can be modeled by Equations 4–6, where 'iei '(i=1..3) denotes the interaction effects among independents conditionally on the prevailing states in the environment (env) (as determined by regulation, economy, and climate). Based on Figure 1, we constructed Equation 1, where the performance was fit to strategy, structure, and BDA to be aligned to the corporate environment:

$$\mathrm{EVA} = \mathrm{f}(\mathrm{struct}, \mathrm{strat}, \mathrm{ie_i}, \mathrm{BDA}\ |\mathrm{env}) \quad (1)$$

$$\mathrm{struct} = \mathrm{f}(\mathrm{form}, \mathrm{com}, \mathrm{cen}, \mathrm{co}, \mathrm{con}) \quad (2)$$

$$\mathrm{strat} = \mathrm{f}(\mathrm{flex}, \mathrm{cost}, \mathrm{qual}, \mathrm{div}, \mathrm{dep}, \mathrm{inn}) \quad (3)$$

$$\mathrm{ie_1 = f(strat, struct|env)} \quad (4)$$

$$\mathrm{ie_2 = f(struct, BDA|env)} \quad (5)$$

$$\mathrm{ie_3 = f(strat, BDA|env)} \quad (6)$$

$$\mathrm{EVA = NOPAT - WACC(TA - CL)} \quad (7)$$

$$\therefore\ \mathrm{EVA = (ROIC - WACC)(TA - CL)} \quad (8)$$

Theodorou (2003) provided a detailed explanation and analysis of Equation 2, where the following structural dimensions and variables were presented (Theodorou & Dranidis 2001): formalization, complexity, centralization, coordination, control, reward, and knowledge management. Additionally, a detailed analysis of Equation 3 can be found in Theodorou (2003), where the strategic priorities of the cost, quality, flexibility, dependability, innovation, and customer service were determined in detail. Based on equations (1)(8),

$$\therefore\ (ROIC - WACC)(TA - CL) = f(struct, strat, ie_i, BDA|Env) \quad (9)$$

when:

$$ROIC = \frac{NOPAT}{IC} = (\frac{NOPAT}{R(q_i)})(\frac{R(q_i)}{IC}),\ where\ R(q_i)\ denotes\ revenues\ of\ \mathrm{i = 1, \dots n\ products}$$

where: 'EVA'= economic value added, 'struct'= structure8, 'strat'= strategy, 'BDA'= big data analytics, 'env'= environment (regulatory, competitive and physical), 'flex'=flexibility, 'qual'= quality, 'div'=diversification, 'dep'=dependability, 'inn'=innovation, 'form'=formality, 'com'=complexity, 'cen'=centralization, 'co'=coordination, 'con'=control, 'iei'= interaction effects for i=1,2,3. WACC: is the weighted average cost of capital, TA: total assets, CL: current long-term liabilities (due within a year), and NOPAT: after tax net operating profit available to all stakeholders.

Thus, the CA mainly consists of a production-demand advantage estimated from operating profit margin $\left(\frac{NOPAT}{R(q_i)}\right)$ and capital advantage $(\frac{R(q_i)}{IC})$ estimated from scope economies (returns) and the diversification effect (Theodorou 1996, Theodorou and Florou 2008). Referring to our main Equation (1), a CA is estimated from EVA when the strategy (strat) is switched to diversification and the structure (struct) is switched to flexibility (such as to fit and aligned with the environment), where the following CA equation (ceteris paribus) is derived:

$$\mathrm{R'(q_i)\!:\ R'(p_1q_1, \dots p_nq_n) > R(p_1q_1) + \cdots + R(p_nq_n)} \qquad \text{i:1…n,}$$
$$\mathrm{VC'(q_1, \dots q_n) < VC(q_1) + \cdots + VC(q_n)}$$
$$\mathrm{R'(p_1q_1, \dots p_nq_n) - VC'(q_1, \dots q_n) > R(p_1q_1) + \cdots + R(p_nq_n) - VC(q_1) + \cdots + VC(q_n)}$$
$$\mathrm{\Delta(EBIT) > 0\ \therefore\ \Delta(NOPAT_{i \dots n}) > 0}$$

Where: 'IC'=invested capital, 'p_i'=price of product: i=1…n, 'R (p_iq_i)'= revenues as price by quantity multiplication of product: i=1…n, 'VC'=variable cost, 'EBIT'=earnings before interest and taxes.

Thus, competitive advantage mainly consists of production-demand advantage estimated from operating profit margin $\left(\frac{\mathrm{NOPAT}}{\mathrm{R(q_i)}}\right)$ and capital advantage $\left(\frac{\mathrm{NOPAT}}{\mathrm{R(q_i)}}\right)$ estimated from scope economies (returns) and the diversification effect (Theodorou, 1996, Theodorou and Florou, 2008). Referring to

[8]Further details on each structural (struct) variable, how measured, how determined etc. can be found in Theodorou and Dranidis (2001).

our main equation (1), where competitive advantage estimated from EVA, when strategy (strat) switched to diversification and structure (struct) switched to flexibility (such as to fit and aligned with the environment), the bellow competitive advantage (ceteris paribus) derived:

$$R'(q_i):\ R'(p_1q_1, \ldots p_nq_n) > R(p_1q_1) + \cdots + R(p_nq_n) \qquad \text{i:1...n,}$$
$$VC'(q_1, \ldots q_n) < VC(q_1) + \cdots + VC(q_n)$$
$$R'(p_1q_1, \ldots p_nq_n) - VC'(q_1, \ldots q_n) > R(p_1q_1) + \cdots + R(p_nq_n) - VC(q_1) + \cdots + VC(q_n)$$
$$\Delta(EBIT) > 0 \therefore \Delta(NOPAT_{i \ldots n}) > 0$$

where 'IC'=invested capital, 'p_i'=price of product: i=1…n, 'R (p_iq_i)'= revenues as price by quantity multiplication of product: i=1…n, 'VC'=variable cost, and 'EBIT'=earnings before interest and taxes.

Scope economies and the operation's CA are derived as $\Delta(EVA) > 0$, since scope economies have a jointed effect of revenues increase (R'>R) and at the same time variable cost decrease (VC'<VC).

The value must be adjusted to the diversification economies derived by a negative or very low correlation among the product portfolio, both for quantities and revenues (Ri, j are the revenues of qi, j products, respectively): $Corell_{qi,qj}\sigma_{qi}\sigma_{qj}$ and $Corell_{qi,qj}\sigma_{qi}\sigma_{qj}$ respectively, driving the idiosyncratic risk lower:

$$\sigma_q = \sqrt{\sum_{i=1}^{n} \sigma_{qi}^2\, \%_{qi}^2 + 2\sum_{i=1}^{n}\sum_{j=i+1}^{n} Corell_{qi,qj}\sigma_{qi}\sigma_{qj}\, \%_{qi}\%_{qj}}$$

$$\sigma_R = \sqrt{\sum_{i=1}^{n} \sigma_{Ri}^2\, \%_{Ri}^2 + 2\sum_{i=1}^{n}\sum_{j=i+1}^{n} Corell_{Ri,Rj}\sigma_{Ri}\sigma_{Rj}\, \%_{Ri}\%_{Rj}}$$

$$EBIT^{adj} = \frac{\Delta(EBIT)}{(\sigma_q)^2 + (\sigma_R)^2}, \qquad NOPAT^{adj} = \frac{\Delta(NOPAT_{i \ldots n})}{(\sigma_q)^2 + (\sigma_R)^2}, \qquad EVA^{adj} = \frac{\Delta(EVA)}{(\sigma_q)^2 + (\sigma_R)^2} \qquad (10)$$

Where: '%': denotes the percentage of each product quantity in total "i, j" portfolio of quantities of relevant revenues "R".

Thus, Equation (1) can be adjusted by Equation (10) as shown below:

$$EVA^{adj} = f(struct, strat, ie_i, BDA|env) \qquad (11)$$

Structure and strategy variables were defined in Equations (2) and (3), while the financial aspect of the CA was defined in the left part of Equation (11). It must be mentioned that the firms' value (EVA^{adj}) must be estimated while taking the forward-looking values into account, instead of only taking the accounting-book based value into account.

Since the relation among the CA and BDA is not a straight linear and not always positive, a maximization criterion needs to be applied. The relationship among the BDA and the CA can be either positive, negative, or cubic curvilinear according to contingencies and the time span of the study (long-term, medium-term or short-term). The curvilinear can be either convex or concave of a U-shaped or V-shaped. Thus, an optimization technique needs to be applied to this tradeoff to maximize the value of Equation (11) per a unit of risk:

$$\text{Max}\ [\text{EVA}^{\text{adj}}]: \max\ [\text{EBIT}^{\text{adj}}(1-\text{t}) - \text{WACC}(\text{TA}-\text{CL})] = \text{f}(\text{struct}, \text{strat}, \text{ie}_{\text{i}}, \text{BDA}|\text{Env}) \quad (12)$$

where: 't' denotes tax rate in percentage.

Now we come up with a mathematical formulation of the conceptual model that enhance decisions regarding BDA (left part independents in Equation 11) to maximize the firms' value (right part/dependent).

The above equations (σp σR) of portfolio risk for products and revenues are based on the Markov portfolio theory. However, relevant optimization techniques cannot be easily used for our case, since Equations 2 & 3, embedded into EVA maximization (Equations 11 & 12), are categorical. Genetic algorithms provide an imperative in such a problems and can be easily found in Matlab and Mathematica.

Based on Equation 12, the generic queries that can now form and guide BDA decisions can be set, as shown below:

Q1: Which BDA technologies and techniques maximize the CA?

Q2: Which structural forms of BDA technologies and techniques maximize the CA (Equations 5 and 12)?

Q3: Which BDA technologies and techniques strategically (strategic targets enablers) maximize the CA (Equations 6 and 12)?

Q4: Which strategic choices interact best with BDA to maximize the CA (Equations 6 and 12)?

Big data technologies mainly refer to the cloud and data base storing, while BDA mostly refers to mathematical and statistical modeling and advance information technology (IT) methods such as those found in AI and neural networks (Theodorou & Karyampas 2007). Specifically, the following technologies are those mostly known nowadays, which can be adjusted on the six-step process of BDA as developed by Google:

1. Data Management platform & Storage: AWS, Azure, Google Cloud, Hive (data warehouse), Datalakes, Spark, SaaS, Salesforce, Xplenty, DSwarm, PIMCore, Hadoop, MySQL, CASSSANDRA, MONGO-DB (NoSQL), Apache HBASE, ORACLE, etc.
2. Cleaning Data: Software live, OpenRefine, Python (pandas), DattaLadder, Trifancta Wrangler, etc.
3. Analyze Data, Computational Knowledge, Stat&Quant Social Net Analysis, Sentiment Analysis, Descriptive, Diagnostic, Predictive, Prescriptive, Splunk (log Analysis), Apache Spark, Hadoop (map reduce), Hive?, SAS, SPSS, etc.
4. Sharing Data, Visualization Google Charts, Tableau, Data Wrapper, Infogram, Python, R, Java, Kafka (messaging), Power BI, Qlik sense, AWS Quicksight, Looker, etc.
5. Scripting Pig, Talent (soft integration), R, Python, Matlab etc.
6. Dashboards & KPI's databox, dasheroo, Grafana, Freeboard, Dashbuilder, etc.

Together, the aforementioned Queries 1–4 along with the six-step process projection of technologies can guide the strategic and structural implementation and adoption of the BDA framework to maximize the firm's value and the CA. Applications will be selected and designed to support those strategies and fit with those structural forms to increase the CA.

4. Conclusions

Based on what Greek ancient philosophy implies about quality (since 333BC), an attempt has been made to focus on data volume (i.e., big data per se). The implication considers the trade-off among the value of quality and that of volume ("big" data). The model examined the quality a strategic characteristic within a portfolio of strategic choices: dependability, cost, flexibility, etc. (Theodorou, 2003, 2005) to maximize the firm's value (competitive advantage) as estimated by the EVA maximization. This model estimates the optimal interactions among strategy, structure, and BDA to deliver a competitive advantage as the main ingredient for a corporation's success and performance. The construct is mathematically formulated and theoretically conceptualized on the effect of these interactions on the EVA through the minimization of volatility and the attainment of a SA. The model opened the ground for a holistic approach within a business environment and advanced the research on how the strategy and structure of BDA can increase a firm's performance. The model enhanced the planning and strategy of BDA by its holistic character, while the use of specific financial metrics quantified the effects.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

All authors declare no conflicts of interest in this paper

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