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JISIB

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**EDITOR'S NOTE** **VOL 13. NO. 1 (2023)**

# *Unveiling the Value of Competitive Intelligence: Coordinated Communication and Added Value*

Recently, a lot of attention has been paid to several aspects of CI, which influence the decision-making of organizations and the acquisition of competitive advantages. Organizations must leverage data, artificial intelligence (AI), and social capital to enhance their competitive intelligence processes. Social media data, AI and machine learning, big data analytics, dynamic capabilities, and intraorganizational social capital all play significant roles in driving strategic decision-making and improving customer experiences. By integrating these elements effectively, organizations can gain valuable insights, mitigate risks, and stay ahead of the competition.

Organizations can enhance their dynamic capabilities by integrating social media analytics into their competitive intelligence practices, particularly in the stages of information collection and analysis. This integration positively influences the various stages of competitive intelligence (Wu, Q. et all., 2023).

Organizations also expect higher added value and looking for sources of this value in relation to competitive intelligence. This value could be shared between different departments and coordinated by corporate communication. (Ding, J.-L. & Shi, B., 2021).

In this issue, the authors explore internal aspects of organizations and propose models that integrate existing knowledge. These models aim to assist organizations in establishing, assessing, and enhancing their CI practices and theories, ultimately resulting in improved organizational performance.

There are practical implications for various organizations, including academic entities. Existing solutions are designed to help businesses deal with unforeseen events by gathering and transforming data into understandable information. While major companies have adopted big data analytics systems, the adoption and effects of business intelligence tools in universities and organizations are not well understood. Therefore, researchers are investigating how business intelligence tools specifically impact decision-making and performance in public universities.

Furthermore, there has been a growing recognition of the importance of startups in driving economic growth and innovation. Governments, private organizations, and academic institutions around the world have initiated various programs and initiatives to support startups, facilitate their establishment, and harness their potential for generating a significant impact on national economies.

These initiatives aim to provide startups with the necessary resources, knowledge, and networks to thrive in competitive markets. The overarching goal is to create an environment conducive to entrepreneurial success and encourage the growth of startup ecosystems.

Within this context, competitive intelligence has emerged as a valuable tool for startups to improve their company performance and gain a competitive edge. Researchers have conducted studies highlighting the role of competitive intelligence in improving company performance through organizational learning.

Finally, there are numerous possibilities for enhancing the applicability of existing tools to address current problems. The use of analytical and adaptive technologies can provide organizations with comprehensive tools and techniques.

I would like to express my gratitude to all contributors to this issue.

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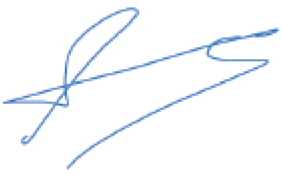

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# Competitive Intelligence Maturity Models: Systematic Review, Unified Model and Implementation Frameworks

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**ABSTRACT** Competitive Intelligence (CI) is vital for sustaining the performance of organisations in an increasingly volatile, uncertain, complex, and ambiguous (VUCA) world. However, the impact of CI on performance is proportional to its maturity level. The article aims to review and integrate the existing literature on Competitive Intelligence Maturity Models (CIMMs) to provide a go-to framework for setting up, assessing, and developing CI. The CIMMs were sourced from scholarly databases, registers, the social web, and using backwards and forward searches. All the CIMMs respecting the characterisation criteria were included in the study. A scientific and empirically validated definition of CI guided the integration and synthesis of the fourteen selected CIMMs. The primary outcome is a proposed unified CIMM (UCIMM) covering all the CI dimensions and aspects in tandem with the respective implementation guidance frameworks. The proposed UCIMM and implementation frameworks effectuate the guidance needed to set up, assess, and develop the CI practice and theory and, ultimately, the performance of organisations.

**KEYWORDS**: Maturity Model; Maturity Levels; Framework; CI Function; CI System; Implementation Roadmap; CI Practice; Organizational Performance

## 1. INTRODUCTION

CI is "the process and forward-looking practices used in producing knowledge on the competitive environment to improve organisational performance" (Madureira et al., 2021a, 2021b). The maturity of the CI practice is positively correlated with being a learning organisation (Senge, 2006). A learning organisation addresses future decision-making proactively, effectively, and efficiently. Within the contingency theory (Fiedler, 1964; Vroom & Yetton, 1973), organisations use decision-making to achieve a strategic fit with their competitive environment (Duncan & Weiss, 1979). The better the decision-making, the greater the fit and the organisational performance (Eisenhardt, 1989). Therefore, CI maturity is both an antecedent and a proxy for organisational performance.

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In the current zeitgeist of a VUCA world with an exponentially increasing speed of change (Bennett & Lemoine, 2014), obtaining and maintaining the strategic fit to sustain top performance is the ultimate challenge. CI is thus vital to navigating highly challenging environments, remaining competitive (Harkleroad, 1998; Hedin, 2005; Vedder & Guynes, 2001), and ensuring the superior performance of organisations (Yap et al., 2018, 2013; Yap & Rashid, 2011). The problem arises in maintaining a CI maturity level that allows organisations to deal with change. Kahaner (1997) has long identified the critical change drivers as the increasing business pace, information overload, more aggressive and global competition, geopolitical changes, and rapid technological change. Nassim Taleb (2007) provided further insight into their volatility and unpredictability. Recent academic and business research corroborates and reinforces the severity of the impact on both organisations and the CI practice (Heppes & Du Toit, 2009; Calof et al., 2017; M-Brain et al., 2019; Klue & SCIP, 2021; ACI & Gilad, 2022; Crayon & SCIP, 2022). As a result, CI evolves up to the average maturity level (Hedin et al., 2014; Heppes & Du Toit, 2009; M-Brain et al., 2019). Organisations must be able to address these impacts in setting up, assessing, adapting, and developing the CI maturity level to obtain top performance. Therefore, the CIMM, consisting of several archetypal levels of achievement across the different dimensions and aspects, is a critical assessment and guidance tool supporting the CI practice evolutionary path.

Previous literature consists of tens of CIMMs. The development approaches for these models range from identifying best practices (APQC et al., 2004; Calof, 1998; J. P. Herring & Leavitt, 2011; Marceau & Sawka, 1999) to assessing cutting-edge CI functions (CIF), programs (CIP), or systems (CIS) (Heppes & Du Toit, 2009). Academic investigations (Calof, 1998; Oubrich et al., 2018), executive opinion (Marceau & Sawka, 1999), practitioners' self-assessments (Comai & Prescott, 2007), and CI experts' professional judgment vendor-sponsored studies (M-Brain et al., 2019) have been the formats of choice in evaluating the professional status and developmental progress of the CI practice. Benchmarking versus an independently established model (Hedin et al., 2014) and case studies are the most frequently used methods (J. P. Herring & Leavitt, 2011). However, CI dimensions and descriptors, as well as the maturity levels used, vary considerably. Most importantly, MMs are not exhaustive regarding the CI dimensions and aspects. As a result, given the broad range of existing CIMMs, it is incredibly challenging to compare and identify the relevant model to use for improving practice or scientific research. Furthermore, no CIMM fully aligns with the conceptual definition of CI, its longitudinal evolution over time, or its full array of dimensions and aspects. These difficulties profoundly impact the scientific development of the CI practice, especially in smaller and less mature organisations. Thus, researching a unified scientific CIMM (UCIMM) is extremely important for effective practical guidance to address the conflicting interests of academics, executives, practitioners, and vendors.

This study aims to fill this gap by performing a systematic literature review – using an explicit, systematic method for identifying, analysing, integrating, and synthesising the findings of prior research – contributing to the conceptualisation of CIMM research. This conceptualisation will allow for integrating relevant descriptors across all dimensions and levels of maturity into a holistic go-to UCIMM. The expected empirical contributions from such a unified model are the significant improvement of decision-making quality and the consequent business performance, the implementation guidance for the effectuation of the CI practice or function, and the increased productivity of CI professionals. Furthermore, the grounding of this theory development exercise in sound theoretical and empirical evidence will highlight critical gaps and paths to exploit while dismissing outdated, irrelevant and duplicate research (Webster & Watson, 2002). Our systematic review based on scientific, commercial and grey literature is expected to deliver on this objective.

The following section details the systematic literature review procedure according to the PRISMA statement (Page, McKenzie, et al., 2021). Results will then be critically analysed and discussed, and a UCIMM will be proposed in the sections that follow. Finally, we conclude with implications and recommendations for application and further research avenues for this topic and the CI field.

## 2. LITERATURE REVIEW

To identify and characterise the relevant CIMMs published in the last three decades, we conducted the systematic review as outlined in table 1:

**Table 1.** Overview of the literature review based on PRISMA, Cooper and Webster & Watson Guidance (Cooper, 1988; Page, Moher, et al., 2021; Webster & Watson, 2002)

| Item | Description |
|---|---|
| Scope | Focus on CIMMs as research outcomes and practices or applications from all types of literature. However, only CIMMs that meet the MM characterisation are within scope (cf. Section 3.2). |
| Goals | Identify, synthesise, and integrate existing CIMMs into a unified holistic CIMM (UCIMM) to support the development of a common linguistic framework covering all CI dimensions per the 5Ps (Madureira et al., 2021a). |
| Perspective | Espousal of position in demonstrating the value of integrating existing CIMMs with the 5Ps of CI. |
| Coverage | Exhaustive as it intends to be "comprehensive in the presentation of works relevant to the topic" (CIMMs). |
| Organisation | Historical in combination with CIMMs content analysis (Cooper, 1988). |
| Audience | CI scholars, CI practitioners, CI vendors, business executives, policymakers |
| Time frame | CIMMs literature published after 1980. |
| Conceptualisation | CI, MM, CIMM (cf. Section 2). |
| Search strategy | Combination and proximity of the search terms "maturity model" and "competitive intelligence" to ensure the exhaustiveness as mentioned above. |
| Sources | Database (DB), registers, CI journals (i.e., CIR and JISIB), and social web as we expect to find CIMMs from practitioner and commercial sources. |
| Procedure | Data was collected, analysed, synthesised and integrated by a single author to avoid reviewer bias for approximately one year between January and December 2022.<br>DB search: Google Scholar, ScienceDirect (Scopus), AB/Inform (Proquest), JSTOR, Emerald Publishing, EBSCO (Business Source Ultimate).<br>Specific CI Journals: Competitive Intelligence Review.<br>Registry search: SCIP.org (Strategic and Competitive Intelligence Professionals).<br>Social web search: use Google Search to identify leading practitioner and commercial literature [i.e., CI vendors (services and technology/software) CIMMs].<br>These sources cover journals, books, conference proceedings, and practitioner sources (Brocke et al., 2009).<br>Backwards and forward search: reviewing the citations found in articles from the first step; "to identify articles citing the key articles identified in the previous steps" (Webster & Watson, 2002).<br>All steps: examine at least titles, abstracts, and introductions in order to evaluate only relevant sources (Brocke et al., 2009). |
| Outcome | The anticipated outcome is an identification of the main CIMMs, their dimensions, and their aspects. We followed the guidance of Cooper (1988) to "combine organisations, […] by addressing works historically within a given conceptual framework." The chosen framework is the 5Ps (dimensions and descriptors) from the CI unified view and modular definition (Madureira et al., 2021a). To the best of our knowledge, still "no classification system for CIMMs exists to date." Therefore, for the content analysis of the MMs, we use a concept-centric approach based on so-called concept matrices (Webster & Watson, 2002). |

## 2.1. Definition of Key Variables and Study Boundaries

### 2.1.1. Competitive Intelligence

Until recently, the definition of CI was not consensual and changed over time, as the previous five universal definitions demonstrate (Bartes, 2014; Breakspear, 2013; Brody, 2008; Marcial, 2018; Pellissier & Nenzhelele, 2013). However, Madureira et al. (2021a) developed a unified view and modular definition, the only empirically validated one (Madureira et al., 2021b). Furthermore, this definition provides the 5Ps – the core defining dimensions and respective descriptors – which may be used as a proxy for assessing the comprehensiveness of a CIMM. As such, we will use this working definition alongside its visual abstract as the guide for comparing and integrating the different CIMMs analysed in the literature review.

### 2.1.2. Maturity Models

Maturity is "the state, fact, or period of being mature" (Oxford English Dictionary, 2022a). As such, it implies the existence of an evolutionary process to achieve the desired end-state. A model is a simplified representation of reality used as an example to follow or imitate (Oxford English Dictionary, 2022b). A Maturity Model (MM) details the evolution levels (also known as stages or phases) of maturity across several structuring dimensions and their respective aspects. Levels have differentiating descriptors providing the purpose and detailed characterisation of each level. Dimensions are areas of capability that structure the object of the model. Each dimension is subsequently structured into several aspects (also known as elements, activities, or measures) for each level (Bruin et al., 2005; Fraser et al., 2002). MMs serve as guide rails to the set-up and development path to achieve the targeted maturity level (Fraser et al., 2002). Lahrmann & Marx (2010) characterised MMs as shown in Figure 1.

| Criteria | Characteristics | | |
|---|---|---|---|
| Dimensions | One-dimensional | Multi-dimensional | Hierarchical |
| Maturity principle | Continuous | Staged | |
| Number of audiences | Single | Multiple (configurations) | |
| Assessment approach | Qualitative | Quantitative | |

**Figure 1.** Fundamental characterisation of MMs (Lahrmann & Marx, 2010, tbl. 1)

In this regard, we will base our study on a few considerations. First, De Bruin et al. (2005) guidance suggests that dimensions should be exhaustive and distinct. Second, MMs have single or multiple dimensions but can also be hierarchical. Hierarchical MMs are more complex and require a formal architecture of measures (Lahrmann & Marx, 2010). Third, staged MM models require compliance with all the dimensions (Fraser et al., 2002), the specified goals and critical practices to reach the aimed level. Fourth, although we acknowledge the different MM audiences, this paper aims to provide industry-agnostic maturity recommendations. Finally, the maturity level assessment can be qualitative using descriptions or quantitative using Likert-like scales (Fraser et al., 2002).

### 2.1.3. Competitive Intelligence Maturity Model

CI maturity relates to the process of thoroughly developing its practice across all dimensions for each level of the model. This maturity can be computed in levels (staged model) or configurations (continuous model). Considering the previous sub-sections, the CIMM guides both the effectuation, the maturity assessment, and the improvement of the CI practice. Thus, CI maturity indicates the level of development for each of the 5Ps (dimensions) and respective descriptors for a predefined audience, organisation, industry, or country. Notable, CIMMs allow economic agents to assess, understand, and improve their performance. Finally, given that CI is multidisciplinary, the CIMM is a broader-scoped umbrella maturity model. As such, this study considers only CIMMs, not Business Intelligence, Market Intelligence, Data Management, Social Intelligence, or Capability Maturity Models (CMMs), as those would be specific and not representative of the overall CI concept.

## 3. The CIMMs STATE OF THE ART

### 3.1. Literature Search Results

The search focused on six scholarly databases (DB), one register (SCIP.org), one specific journal (Competitive Intelligence Review), the Social Web, and Citation Searching (i.e., snowballing). We screened all the results except for Google Scholar and Google Search, where we stopped at the saturation point, i.e., no more showing of relevant or duplicate CIMMs. We successfully retrieved all the 38 records sought and screened for relevant CIMMs matching the scope (cf. Table 1) and MM characterisation (cf. Figure 1). Snowballing – backward and forward search – allows us to identify five additional records. Scholarly DBs and registers allowed us to elite eight reports while other methods identified six further. The outcome was fourteen reports included in this study (Figure 2).

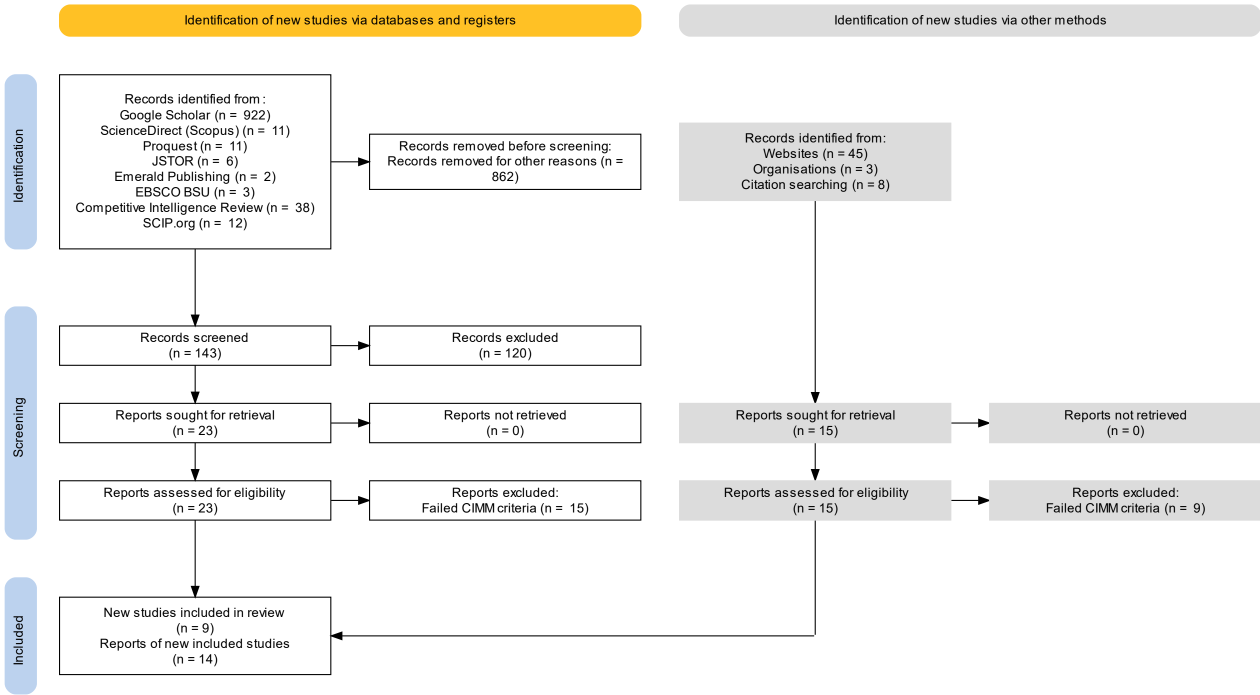


**Figure 2.** PRISMA 2020 flow diagram used for the systematic review (Page, Moher, et al., 2021)

## 3.2. Overview of the selected CIMMs

The overview goes beyond the criteria from Section 2-1 by adding supporting scientific or empirical evidence and the motive supporting the development of the CIMM (Table 2). We included a further detailed characterisation in Annex 2. A CIMM is developed every year and a half in the defined 1980-2022 timeframe denoting the longitudinal importance of the topic. The CIMMs have 4,1 levels (computed for staged maturity principle) and 6,4 dimensions on average. They are primarily qualitative, based on case studies or surveys, and focused on assessing and improving the CI function or programmes. Only one CIMM (M-Brain et al., 2019) is motivated by increasing the performance of organisations, which is the ultimate purpose of CI (Madureira et al., 2021a, 2021b).

**Table 2.** Detailed characterisation of included CIMMs (developed by the authors)

| (Authors, Year) Citation | Name of the CIMM | Dimensions | Maturity Principle | Number Of Audiences | Assessment Approach | Study / Report | Motivation |
|---|---|---|---|---|---|---|---|
| (Calof, 1998) | Competitive Intelligence Quotient (CIQ) | Multi-dimensional: 4 | Continuous to Maturity (WCCI) | Multiple | Qualitative | Report | Economic Policy |
| (Marceau & Sawka, 1999) | World-Class CI Program in Telecoms (WCCIP-T) | Multi-dimensional: 5 | Continuous | Single (Telecom) | Qualitative | Study of Telecoms practices | CI Program development framework |
| (Prescott, 1999) | Action-Oriented CI Program (AOCIP) | Multi-dimensional: 5 + 5 | Staged: 4 | Multiple: Proposal Management Professionals focus | Qualitative | Report based on APQC 1997 Best Practices study | Improve CI effectiveness |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| (West, 2001) | CI Stages of Development (CISoD) | Multi-dimensional: 4 | Staged: 3 | Multiple: European focus | Qualitative | Report | CI usage development |
| (APQC et al., 2004) | FIICH Model (FIICH) | Multi-dimensional: 5 + 21 | Staged: 4 | Multiple | Qualitative | Study of CI best practices | Guide CI efforts leveraging empirical best practices |
| (J. P. Herring & Leavitt, 2011) | CI Maturity Matrix (CIMMx) | Multi-dimensional: 5 | Staged: 5 | Multiple | Qualitative | Case Study | Implement and develop CI best practices |
| (Comai & Prescott, 2007) | World Class CI (WCCI) | Hierarchical: 9 + 48 | Continuous: 1-5 | Multiple | Mixed. Mostly Quantitative | Study | Identify the Dimensions, Level and Drivers for WCCI |
| (Singh et al., 2008) | Roadmap for Enduring CI Success (RECIS) | Multi-dimensional: 11 | Staged: 4 | Multiple. Additional focus on Pharma | Qualitative | Study based on Worldwide CI Survey | Ensure CI success |
| (Heppes & Du Toit, 2009) | CI Function Maturity Level (CIFML) | Multi-dimensional: 8 | Staged: 3 | Single (Banking) | Qualitative | Case Study | Establish the CIF maturity level within a South African retail bank |
| (J. P. Herring & Leavitt, 2011) | World-Class CI Program Roadmap (WCCIPR) | Multi-dimensional: 4 | Staged: 3 | Multiple | Qualitative | Report | Show CIF evolution and promote Organisational Learning |
| (Hedin et al., 2014) | World Class MI Roadmap (WCMIR) | Multi-dimensional: 6 | Staged: 5 | Multiple | Mixed. Mostly Quantitative | Report based on own global survey | Guide the development of the CI function |
| (Oubrich et al., 2018) | Competitive Intelligence Maturity Model (CIMM-M) | Multi-dimensional: 6 | Staged: 3 | Multiple. Focused on Morocco. | Mixed. Mostly Quantitative | Report based on own local survey | Identify the purpose and propose a CIMM to assess Morocco CI practices |
| (M-Brain et al., 2019) | M-Brain - World-Class Intelligence Framework (WCIF) | Multi-dimensional: 9 | Staged: 5 | Multiple | Mixed. Mostly Quantitative | Report based on own global survey | Help organisations improve business performance |
| (Alvares et al., 2020) | Organisational Intelligence Maturity Model (OIMM) | Hierarchical: 2 + 17 | Staged: 6 | Multiple | Qualitative | Report | Understand, implement, improve, benchmark or self-assess IM, KM, or CI models. |

### 3.3. CIMMs benchmark vis-à-vis the CI 5Ps and descriptors

We analysed and compared the content of the selected CIMMs vis-a-vis the dimensions (5Ps) and descriptors of the CI unified view and modular definition scientifically validated by Madureira et al. (2021a, 2021b). As such, the visual abstract of the paper (Madureira et al., 2021a) provided a standardised meta-model (Lahrmann & Marx, 2010) for content analysis (conceptualisation, codebook creation, coding, refinement, and reliability check), guaranteeing the scientific rigour of the classification process (Neuendorf, 2019). Furthermore, the Webster & Watson (2002) conceptual-centric approach allows for the comparison between the CIMM's meta-model (dimensions and aspects) and the 5Ps (Purpose, Purview, Practices, Process, and Product) and underlying descriptors – Table 3. In its preparation, we paid particular attention to three potential issues. First, synonymy – different names for the same dimension/aspect. Second, polysemy – same name but meaning different dimensions/aspects. Last, homonymy – similar names suggesting similar dimension/aspect but effectively meaning different dimensions/aspects. Additionally, we needed to make several assumptions:

- the tools and techniques can refer to the Process or the Product dimensions – e.g., Analysis of Competing Hypothesis (ACH) can either refer to the technique used in the process of analysis or the product of such analysis, the CI deliverable;
- that we correctly empathised with the meaning the author intended to convey from reading the original article;
- that some CIMM dimensions need to be split (hence appearing in two or more columns in table 3 below) for two reasons:
    1) CIMMs included aspects that correspond

to different benchmarked dimensions (Madureira et al., 2021a) – e.g., the ”strategic significance” dimension from Comai & Prescott (2007) has aspects of three of the 5Ps, Purpose (usage in strategy development), Purview (focus on the strategic scope), and Practices (CI is included in the corporate strategy statement);

2) they refer to various dimensions or aspects in different maturity levels.

**Table 3.** Integration and benchmark of included CIMMs vis-à-vis the Unified View and Modular Definition of CI (Madureira et al., 2021a)

| (Authors, Year) Citation | Name of the CIMM | CI Dimensions and (aspects) | | | | | Model Maturity Levels |
|---|---|---|---|---|---|---|---|
| | | Purpose | Purview | Practices | Process | Product | |
| (Calof, 1998) | Competitive Intelligence Quotient (CIQ) | | Activities (scope) | Style<br>Resources | Activities (reporting, sources) | Tools | 1. Infancy<br>2. Maturity/World Class |
| (Marceau & Sawka, 1999) | World-Class CI Program in Telecoms (WCCIP-T) | Decision-support (opportunities)<br>Culture (early warning) | | Process (interface, location)<br>Culture (info sharing) | Process (key activities, interface)<br>Decision-support (options)<br>Technology (storage) | Decision-support (portfolio, tools techniques)<br>Technology (infrastructure) | World Class (continuous) |
| (Prescott, 1999) | Action-Oriented CI Program (AOCIP) | Focus | | Location & structure (personnel)<br>ethics | Location & structure (network)<br>Projects | Products (TAR) | 1. Gathering<br>2. Industry & competitor analysis<br>3. Strategic decision making<br>4. Core capability |
| (West, 2001) | CI Stages of Development (CISoD) | Applications (anticipation) | | Organisation<br>Applications (curiosity) | Data Collection | CI Systems | 1. Aware<br>2. Sensitive<br>3. Intelligent |
| (APQC et al., 2004) | FIICH Model (FIICH) | Change (performance)<br>Focus (goals & objectives) | | Implement<br>Institutionalise<br>Change (behaviour) | Hone<br>Change (process) | | 1. Prestart-up<br>2. Start-up<br>3. Established<br>4. World Class |
| (J. P. Herring & Leavitt, 2011) | CI Maturity Matrix (CIMMx) | Processes (aligned) | | Teams<br>Tools (Training)<br>Processes (culture, ethics, legal) | Processes (gathering, cyclic)<br>Techniques (KITs, Sources, Analytical) | Products<br>Tools (Techniques, tools) | 1. Ad-hoc<br>2. Emerging<br>3. Defined<br>4. Institutional<br>5. Optimised |
| (Comai & Prescott, 2007) | World Class CI (WCCI) | Strategic significance<br>CI in SBU (vision) | Project selection<br>Strategic significance | Human resources<br>Evolution<br>Governance<br>Culture<br>Process (protocol)<br>Resources (financial) | Projects<br>Process (sub-processes)<br>CI in SBU (procedure, governance) | CI in SBU (portfolio)<br>Resources (system, software) | 1. Not started<br>2. Some progress<br>3. Still a lot to do<br>4. Nearly achieved<br>5. Fully achieved |
| (Singh et al., 2008) | Roadmap for Enduring CI Success (RECIS) | | | People<br>Analysis (capability)<br>Professionalism<br>Organisational structure<br>Roles & responsibilities<br>Awareness<br>Value perception | Processes<br>Research<br>Analysis (insight) | Technology | 1. Stick fetching<br>2. Pilot<br>3. Proficient<br>4. World Class |

| **(Authors, Year) Citation** | **Name of the CIMM** | **CI Dimensions and (aspects)** | | | | | **Model Maturity Levels** |
|---|---|---|---|---|---|---|---|
| | | **Purpose** | **Purview** | **Practices** | **Process** | **Product** | |
| (Heppes & Du Toit, 2009) | CI Function Maturity Level<br>(CIFML) | Relationship w/ management (strategy, early warning, opportunities)<br>Deliverables (strategy) | | Relationship w/ management (C-suite)<br>Staffing<br>Skills & training | Relationship w/ management (decision)<br>Capabilities<br>Analytical products<br>Sources of Information<br>Info requirements | Deliverables | 1. Early stage<br>2. Mid-level<br>3. World Class |
| (J. P. Herring & Leavitt, 2011) | World-Class CI Program Roadmap<br>(WCCIPR) | Policies (mission, alignment)<br>Uses (strategic planning, strategy, benchmark)<br>Methods (early warning, threats) | | Professional development<br>Policies (governance, mission)<br>People<br>Users (training)<br>Methods (future studies)<br>Uses (long-range planning) | Processes (CCI)<br>Procedures (KITs)<br>Methods (sub-processes)<br>Users (networks)<br>Sources | Users & uses (products)<br>Methods (products, expert systems, software)<br>Processes (value added) | 1. Developmental<br>2. Professionalisation<br>3. Optimisation |
| (Hedin et al., 2014) | World Class MI Roadmap<br>(WCMIR) | Scope (purpose) | Scope (macro, meso, user groups) | Organisation<br>Culture | Process<br>Tools (templates, techniques) | Deliverables<br>Tools (CI system) | 1. Firefighters<br>2. Beginners<br>3. Coordinator<br>4. Directors<br>5. Futurists |
| (Oubrich et al., 2018) | Competitive Intelligence Maturity Model<br>(CIMM-M) | Impact | Relationship w/ management (functions) | Resources<br>Structure<br>Strategy & culture | System<br>Analytical<br>Deliverables<br>Capabilities<br>CI Use<br>Relationship w/ management (actionable) | | 1. Early stage<br>2. Mid-level<br>3. World Class |
| (M-Brain et al., 2019) | M-Brain - World-Class Intelligence Framework<br>(WCIF) | Leadership<br>Scope (strategic objectives, opportunities, early warning) | Scope (external environment) | Organisation<br>Culture<br>Management<br>Scope (forward-looking) | Process<br>Stakeholders<br>Digitalization | Deliverables<br>Tools | 1. Informal<br>2. Basic<br>3. Intermediate<br>4. Advanced<br>5. World Class |
| (Alvares et al., 2020) | Organisational Intelligence Maturity Model<br>(OIMM) | | | Org. learning (capability)<br>Org. capabilities<br>Org. memory (capability)<br>Spaces<br>Info. policy<br>Culture<br>Individual Vision<br>Env. scanning (practice) | Env. scanning (process)<br>Storage, search, recovery<br>Sharing & re-usage<br>Usability (use)<br>Org. memory (storage)<br>Security<br>Org learning (process) | Knowledge value<br>Knowledge and info processes<br>Intel. reports<br>Usability (system)<br>Technology | 1. Initial<br>2. Intermediate<br>3. Advanced |
| **CIMMs w/ dimension** | Σ | 11 | 5 | 14 | 14 | 12 | **Average Levels:** 3,9 |
| **Dimension Alignment** | % | 78,6% | 35,7% | 100% | 100% | 85,7% | **Total Benchmarked Aspects:** 33 |
| **Aspects average alignment** | % | 30,0% | 11,9% | 42,9% | 33,8% | 31,3% | |
| (Madureira et al., 2021a) | Competitive Intelligence Unified and Modular Definition (adapted from Visual Abstract for benchmarking) | Performance<br>Decision (specific goals, competitive advantage, early warning) | Competitive environment<br>External (macro, meso, micro)<br>Internal (org. functions) | Org. practices<br>Capabilities (individual, organisational, structure, policies, mindset, culture)<br>Orientation (time horizon) | Activities<br>Procedure (processes, characteristics) | Knowledge<br>Nature (augmented, machine, human)<br>Outcome (knowledge management, characteristics) | |

## 4. DISCUSSION OF FINDINGS

The following sub-sections detail the findings from the integration and benchmarking exercise from the previous section. We start at the dimensional level and then go deeper into the aspects. Finally, we discuss the CIMMs, the implications of the findings, our recommendations for implementation and the limitations of the study.

### 4.1. Dimensions level

An evident gap in the results is that, as with any strategy (Rumelt, 2012, 2022), the underlying reason for the CI efforts should be the starting consideration. However, despite the need for CI practitioners to start with the end in mind, the CI Purpose dimension is the second least addressed in identified CIMMs.

A second finding is that only five CIMMs include the CI Purview dimension and aspects. The scope is critical for the CI practice as it defines the focus and conditions the effectiveness of the activities. It is impossible to develop intelligence for the entire CI scope. In an information-overloaded world, CI professionals must trade off the amount of Big Data (Laney, 2001) processed vis-à-vis the (lack of) computing power and the available headspace. The considerable stream of research on Key Intelligence Topics (KITs) is proof of the importance and guidance on this topic (J. Herring, 2008; J. P. Herring & Leavitt, 2011).

Surprisingly, all CIMMs address CI Practices despite being the least mentioned dimension in the 816 definitions used in developing the benchmarked definition (Madureira et al., 2021a). The importance of the CI Practices for the CIMM is evident since it materialises the concept. The Practices and Process dimensions form the core of the CI model, reinforcing each other in implementing CI effectively. The CI function location in the organisational structure (Calof, 1998; Comai & Prescott, 2007; J. P. Herring & Leavitt, 2011; Marceau & Sawka, 1999; Singh et al., 2008), the policies (namely the importance of respecting the legal and ethical aspects (J. P. Herring & Leavitt, 2011; Prescott, 1999), the capabilities of the organisation and the individual (Alvares et al., 2020; Comai & Prescott, 2007; Oubrich et al., 2018), the mindsets (APQC et al., 2004; Calof, 1998; Comai & Prescott, 2007; West, 2001), and the culture of intelligence (Alvares et al., 2020; Hedin et al., 2014; M-Brain et al., 2019; Oubrich et al., 2018), are the most appointed key success factors in the CIMMs for the development and evolution of CI (Adamala & Cidrin, 2011; Nasri & Zarai, 2013; M-Brain et al., 2019; Marceau & Sawka, 1999).

There is no surprise, though, in the complete alignment between the CIMMs and the CI Process dimension, given that it provides the blueprint for the CI activities performed and overall output.

The lower level of alignment (85,7%) towards the CI Product dimension is somehow more problematic given the importance the quality of CI has on decision-making, which in turn profoundly impacts the performance of organisations.

### 4.2. Aspects level

An in-depth analysis of the aspects (and sub-aspects) evidence a high synonymy, polysemy, and homonymy. Navigating the meaning of the aspects across CIMMs is extremely difficult given its number, the diverse nomenclature used, and the longitudinal evolution of the CI construct (Prescott, 1999). It is almost impossible to benchmark the maturity level between CI functions, programs, organisations, industries or countries using different CIMMs. Therefore, there is a clear need for a unified reference model with standardised nomenclature of dimensions and aspects.

Another important finding is the different levels of the thoroughness of the CIMMs regarding the aspects. On average, for any given dimension, the CIMMs do not address half of the aspects of the unified view of CI. Again, this reinforces the need for a holistic go-to CIMM with a solid scientific base that executives and academics can rely upon in theory and praxis.

### 4.3. CIMMs

A significant finding is that only one CIMM covers the 5Ps. This insight highlights the relevance of this study, addressing the research gap for a go-to CIMM of reference and delivering on the expected contributions. Moreover, by benchmarking the best of theoretical and empirical CIMM knowledge vis-a-vis a unified and scientifically validated definition of CI (Madureira et al., 2021a, 2021b), we bring a solid foundation and scientific rigour to the CI practice, the broad-spectrum CI audiences, and the related disciplines. The findings also contribute to establishing CI science, as an integrated scientifically developed UCIMM will make the practice more scientific, repeatable, and comparable between organisations and industries. On top, none of the literature from the included CIMMs refers to the order of implementation of the 5Ps. Nor are the criteria for dimension selection, exceptions for best practices, or findings from case studies and empirical surveys. The level of arbitrariness can be considerable and dependent on the scope – specific country, industry, or organisation under analysis.

Overall, the findings highlight the essential contributions of the study. Firstly, all the dimensions and aspects included in the CIMMs fit within the CI unified view and modular definition (Madureira et al., 2021a). Nevertheless, there are still descriptors of the CI definition not addressed by aspects in any of the maturity models studied. Consequently, integrating the missing aspects into a CIMM will guarantee that professionals do not oversee any critical aspect and a sound grounding in CI theory. Secondly, there is the need for a more manageable CIMM. Assessing more than five dimensions can be burdensome for practitioners in a more pragmatic business setting. Conveying the results to the top management is also made more difficult as the number of dimensions increases. This miscommunication with top management can endanger the allocation of further needed resources for CI, endangering its development. As such, the hierarchical structuring of all the aspects into five dimensions seems to be a valuable empirical and theoretical contribution. Therefore, given previous CIMM shortcomings, we propose a unified CIMM in the next section.

### 4.4. Integration of CIMMs into a proposed UCIM

We used the Capability Maturity Model Integration (CMMI) developed by the Software Engineering Institute at Carnegie Mellon University to integrate the CIMMs (ISACA, 2022). This process and behavioural model, designed to improve the performance of organisations, share the exact purpose of CI (Madureira et al., 2021b), hence our preferred choice. The model aims to combine multiple business maturity models into one framework, thus additionally addressing the challenge identified in Section 4-3. A model is a tool for streamlining process improvement by developing measurable benchmarks and creating a structure for encouraging productive, efficient behaviour throughout the organisation, functions, and projects. Therefore, it leverages the established standards for vetting vendors and suppliers, identifying and resolving process issues, and minimising risk while building a corporate culture that supports the new integrated model. In addition, the maturity and capability levels of an organisation provide a way to characterise its capability and performance.

#### 4.4.1. Maturity Levels (ML)

MLs represent a staged path for the organisation to improve the performance and processes efforts based on predefined dimensions and aspects. Within each ML, the dimensions and aspects also provide a path to performance improvement. Each ML increments the previous by adding new functionality or increased rigour. The goal is to raise the maturity of the organisation to the highest ML. Once reached, organisations should focus on maintenance and regular improvements, a learning organisation.

The journey starts at ML0 – *Incomplete* – where CI work may or may not get completed. CI goals are not established, and the processes are partly formed or do not meet the needs of the organisation. In ML1 – *Initial* – CI processes are viewed as unpredictable and reactive. CI work gets completed, but it is often delayed or over budget. This is the worst level for an organisation facing an unpredictable environment that increases risk and inefficiency. In ML2 – *Managed* –

organisations achieve the project management level. Projects are planned, executed, measured, and assessed, but many issues remain unaddressed. In ML3 – *Defined* – organisations are more proactive than reactive. A set of organisational policies and standards guide projects, programs, and portfolios. Organisations know their shortcomings, how to overcome them and the objectives for improvement. In ML4 – *Measured* – the organisation starts to measure and control the business, working off quantitative data to determine predictable processes aligned with stakeholder needs. The organisation manages risk with insight-driven process deficiencies. Lastly, in ML5 – *Optimised* – the organisation processes are stable, flexible, and agile. The learning organisation status is achieved with continuous improvement and responding to changes or other opportunities in an innovative and agile way. ML4 and ML5 are considered high maturity and stakeholder and customer-centric.

### 4.4.2. Capability Levels (CL)

CLs are used to evaluate the CI process improvement and performance of the organisation. They bring structure to the process and performance improvement. Each CL builds on the last, in the same fashion as MLs, for appraising an organisation. The CLs range from CL0 – *Incomplete* – with inconsistent performance and incomplete approach to achieving the intent of CI. In CL1 – *Initial* - organisations address performance issues in specific activities, but there is not a complete CI practice in place. Cl2 – *Managed* – there is a complete set of procedures that result in CI practice improvement. Finally, in CL3 – *Defined* – the focus is on achieving project and organisational performance objectives with clear organisational standards for managing CI projects.

### 4.4.3. Dimensions and Aspects

Based on the finding from Section 4-3 that some aspects are present but do not thoroughly cover all the relevant descriptors from Madureira et al. (Madureira et al., 2021a), we focused on adding the missing aspects to the UCIMM. Furthermore, given that the 5Ps and their descriptors are empirically proven, the outcome is a hierarchical catalogue (cf. Figure 3) of mutually exclusive CI maturity dimensions covering all aspects replicating the benchmarked visual abstract (Madureira et al., 2021a).

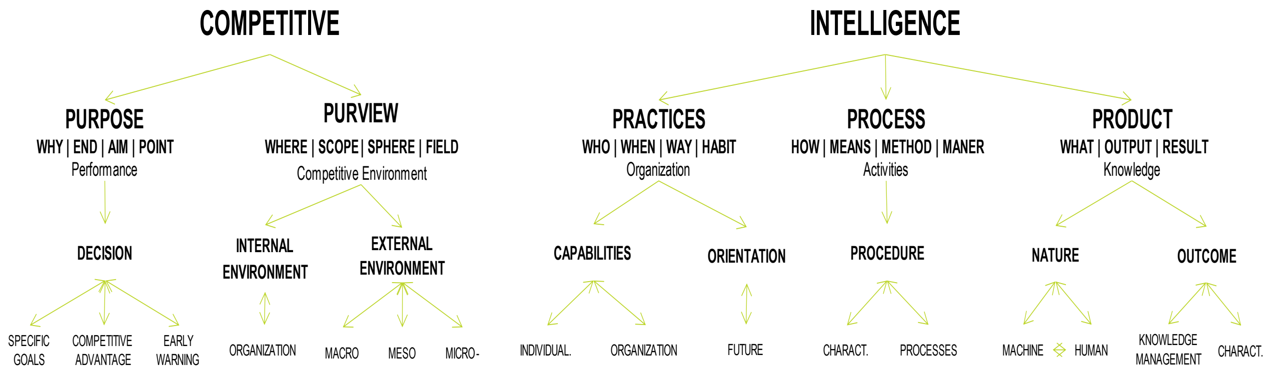


**Figure 3.** UCIMM hierarchical meta-model – dimensions, aspects, and sub-aspects (adapted by the authors)

### 4.4.4. The proposed UCIMM

The UCIMM proposed comprises five levels of maturity, three levels of capability, five dimensions, eight aspects, and sixteen sub-aspects. The UCIMM is multi-dimensional, hierarchical, staged, primarily qualitative and built on the integration of previous studies.

**Table 4**. The UCIMM (prepared by the authors building on Madureira et al. unified view of CI (Madureira et al., 2021a)

| Name of the CIMM | CI Dimensions and (aspects) | | | | | Model Maturity Levels |
|---|---|---|---|---|---|---|
| | **Purpose** | **Purview** | **Practices** | **Process** | **Product** | |
| Unified Competitive Intelligence Maturity Model (UCIMM) | Performance<br>Decision (specific goals, competitive advantage, early warning) | Competitive environment<br>External (macro, meso, micro)<br>Internal (org. functions) | Org. practices<br>Capabilities (individual, organisational, structure, policies, mindset, culture)<br>Orientation (time horizon) | Activities<br>Procedure (processes, characteristics) | Knowledge<br>Nature (augmented, machine, human)<br>Outcome (knowledge management, characteristics) | **Proposed Maturity Levels**<br>0. Incomplete<br>1. Initial<br>2. Managed<br>3. Defined<br>4. Measured<br>5. Optimised |

Following, we propose four integrated graphical visualisations (Figures 4-7) and their explanation to guide and help CI professionals implement the UCIMM in practice.

### 4.4.5. CI Purpose

CI aims to create value by addressing its stakeholder needs in a unique and superior way vis-a-vis its competitors. As such, organisations must continuously make decisions to adapt to the evolving context and stakeholder needs and wants. Stakeholder centricity is pivotal to guaranteeing that the value created is superior to the value provided by competitor organisations at any time. Optimised CI organisations support specific strategic, tactical, and operational decisions, help develop competitive advantages and provide early warning to decision-makers. Thus, the critical constructs are adaptation, agility, and anticipation.

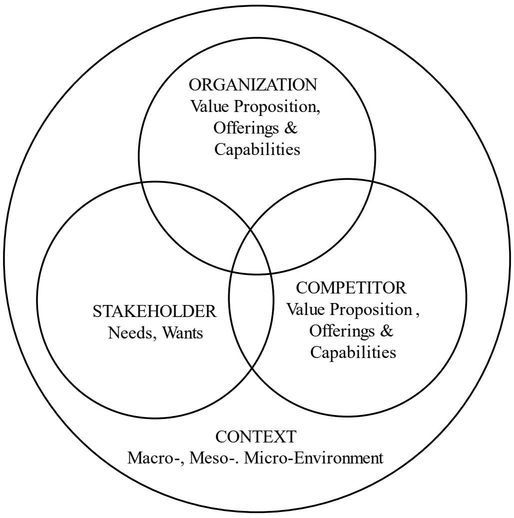


**Figure 4.** CI Purpose (developed by the authors)

### 4.4.6. CI Purview

The scope of CI is the entire competitive environment (Figure 5). It encompasses the macro forces (macro-environment – outer arrows), the market forces (meso-environment – dashed triangle), the industry forces (microenvironment – industry (Porter, 2008)), and the internal environment (inside the organisation – players). Therefore, given its wide dimension, aligning the scope addressed by the CI function with the purpose of the organisation is paramount. Most notably matching the scope to the maturity level of the CI competencies. An eventual mismatch affects the quality of CI, leading to sub-standard decisions and ultimately jeopardising the overall performance. Therefore, the CI practice must start small and increase the scope as its resources and competencies develop.

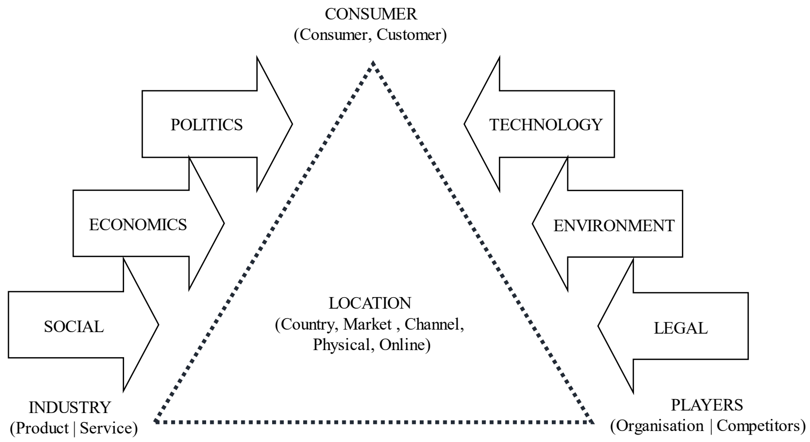


**Figure 5.** CI Purview (developed by the authors)

### 4.4.7. CI Practices and Process

The Core CI Model results from integrating the CI Practices and Process dimensions. Process-wise, learning organisations continuously adapt and improve their processes, tools, and techniques to support high-quality decision-making. The activities in the middle concentric circle (Figure 6) are guided by the CI procedure and executed with project management proficiency. The CI practice (and performed activities) depends on soft and hard factors: the place it occupies in the organisational structure, the policies that guide its execution, the mindsets, and the intelligence culture. The time orientation also impacts CI activities. Understanding the past is not enough; understanding the present may not be possible without considering the past, and anticipating the future is impossible without previous time horizons. Organisations optimising CI are forward-looking, integrating the different time horizons synergically to create a new official future (Wilkinson & Kupers, 2013). In a nutshell, CI needs to be an established support activity within the value chain of the organisation.

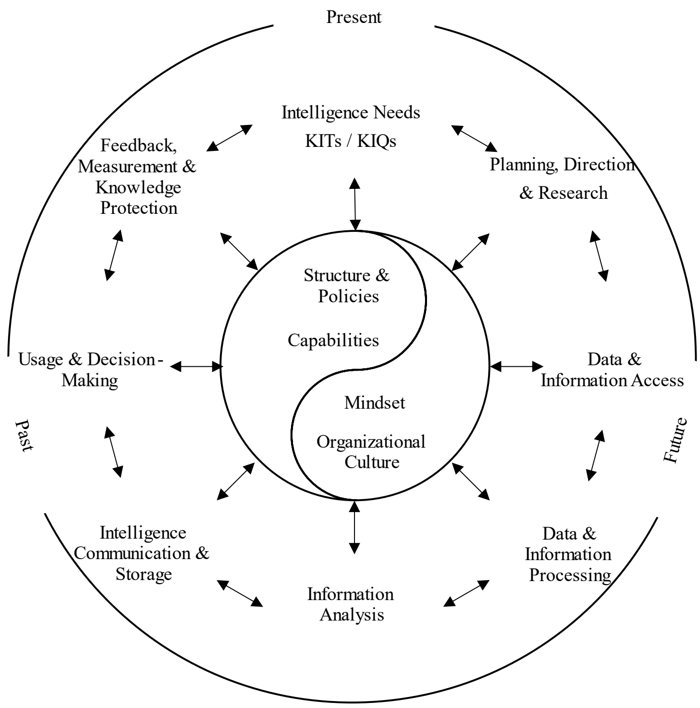

**Figure 6.** Core CI Model: Practices and Process (developed by the authors)

### 4.4.8. CI Product

The output of CI outcome is a set of artefacts (deliverables, systems, or projects) produced for a given purpose, within a specific scope, through a systematic process, and a defined set of practices. Given the need for anticipation, organisations must act on quality intelligence – meaning the actionable insights will be verified true (converted into knowledge) or allow for creating an official future (Wilkinson & Kupers, 2013). Despite knowledge being the desired output, if an organisation waits for the insights to be verified true (e.g., a merger between two competitors), it will lose its opportunity to influence the competitive outcome. As such, CI has no value if the decision-makers receive factual truths. They need actionable insights.

Moreover, the CI functions will derive learnings from using such intelligence and converting them into wisdom. The knowledge and wisdom of today are the data points of tomorrow, allowing CI practitioners to develop new higher-order intelligence. An increasingly important factor is the augmentation of artificial intelligence by CI professionals to guarantee reduced time to insight and overall timeliness of deliverables. Therefore, the CI function must not limit itself to data science or information management and should leverage knowledge management to become a learning organisation (Alvares et al., 2020).

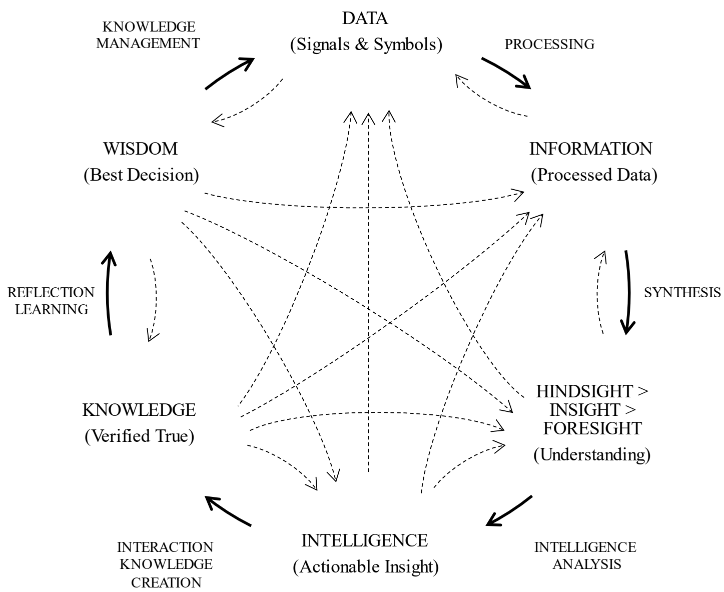


**Figure 7**. CI Product (developed by the authors)

### 4.5. Limitations and future research

We purposely limited the study to CIMMs and excluded models focusing on CI subdomains, such as Business Intelligence MMs, Artificial Intelligence MMs, or Capability MMs. The specific models can thus be integrated for a more thorough and granular assessment, guidelines, and evolutionary path. Namely, AIMMs can be a fruitful and valuable research avenue, given the need for guidance in this newer field within CI. Another research path is the empirical validation of the proposed model, the UCIMM. To this end, developing a scientifically validated scale would be essential.

## 5. CONCLUSION

The study successfully addressed the need to develop a UCIMM for effective practical guidance addressing the conflicting interests of academics, executives, practitioners, and vendors. This study adds to existing theory by synthesising the current CIMMs literature, serving as a future reference for all CI stakeholders. More prominently, it expands CI theory with the first ever integrated CIMM based on a scientific and empirically validated definition of CI. Furthermore, it contributes to practice by identifying gaps in existing CIMMs dimensions and aspects, providing a thorough and scientifically sound UCIMM. The model allows practitioners to pinpoint and address the areas they need to improve.

The accompanying frameworks support a better assessment, implementation, and development of the CI practice in organisations, navigating the adverse impacts of continuous change. Higher quality CI – timely, actionable, accurate, relevant (TAR) (Prescott, 1999) – should result in better decision-making and improved performance of organisations. On becoming a reference model, the UCIMM will save time while guiding the effectuation of CI construct and practice, functions, systems and programmes in surpassing the average and reaching the world-class optimised level of maturity.

## 6. DECLARATIONS

### 6.1. Author Contributions

Conceptualisation, LM, AP, and MC; methodology, LM; formal analysis, LM; investigation, LM; resources, LM; data curation, LM; writing—original draft preparation, LM; writing—review and editing, LM, AP, and MC; visualisation, LM; supervision, AP, and MC; project administration, LM, AP, and MC; funding acquisition, AP and MC. All authors have read and agreed to the published version of the manuscript.

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### 6.3. Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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# ANNEXES

## Annex 1: PRISMA Checklist

**Table 3.** PRISMA 2020 Checklist (Page, McKenzie, et al., 2021)

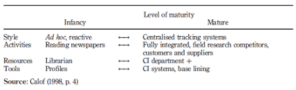
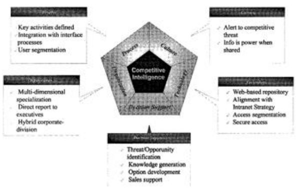
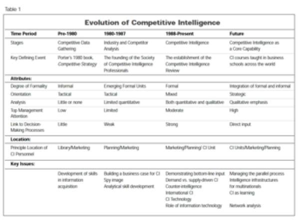
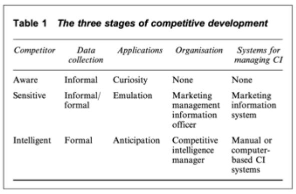
| Section and Topic | Item # | Checklist item | Location where item is reported |
|---|---|---|---|
| **Title** | | | |
| Title | 1 | Identify the report as a systematic review. | **Page 1, line 1** |
| **Abstract** | | | |
| Abstract | 2 | See the PRISMA 2020 for Abstracts checklist. | **Page 1, lines 4-15** |
| **Introduction** | | | |
| Rationale | 3 | Describe the rationale for the review in the context of existing knowledge. | **Page 1-2, lines 45-13** |
| Objectives | 4 | Provide an explicit statement of the objective(s) or question(s) the review addresses. | **Page 2, lines 14-23** |
| **Methods** | | | |
| Eligibility criteria | 5 | Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses. | **Page 2, line 32 - Table 1** |
| Information sources | 6 | Specify all databases, registers, websites, organizations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted. | **Page 2, line 32 - Table 1** |
| Search strategy | 7 | Present the full search strategies for all databases, registers, and websites, including any filters and limits used. | **Page 2, line 32 - Table 1** |
| Selection process | 8 | Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and, if applicable, details of automation tools used in the process. | **Page 2, line 32 - Table 1** |
| Data collection process | 9 | Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and, if applicable, details of automation tools used in the process. | **Page 2, line 32 - Table 1** |
| Data items | 10a | List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g., for all measures, time points, analyses), and if not, the methods used to decide which results to collect. | Page 5, line 6 - Table 2 |
| | 10b | List and define all other variables for which data were sought (e.g., participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information. | Page 5, line 6 - Table 2 |

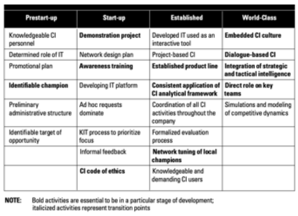
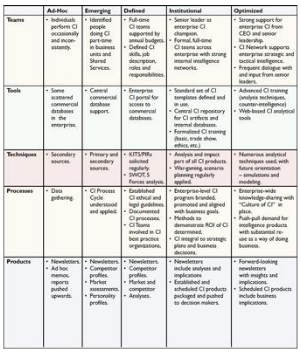
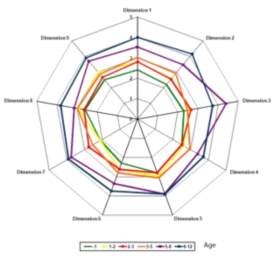
| Section and Topic | Item # | Checklist item | Location where item is reported |
|---|---|---|---|
| Study risk of bias assessment | 11 | Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process. | Page 2, line 32 - Table 1 |
| Effect measures | 12 | Specify for each outcome the effect measure(s) (e.g., risk ratio, mean difference) used in the synthesis or presentation of results. | Page 6, line 27 - Table 3 |
| Synthesis methods | 13a | Describe the processes used to decide which studies were eligible for each synthesis (e.g., tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)). | Pages 6, lines 2-26 |
| | 13b | Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions. | Page 6, lines 2-7 |
| | 13c | Describe any methods used to tabulate or visually display results of individual studies and syntheses. | Page 6, lines 8-10 |
| | 13d | Describe any methods used to synthesise results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used. | Page 6, lines 2-7 |
| | 13e | Describe any methods used to explore possible causes of heterogeneity among study results (e.g., subgroup analysis, meta-regression). | Not applicable |
| | 13f | Describe any sensitivity analyses conducted to assess robustness of the synthesised results. | Not applicable |
| Reporting bias assessment | 14 | Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases). | Not applicable |
| Certainty assessment | 15 | Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome. | Page 6, lines 2-7 |
| **Results** | | | |
| Study selection | 16a | Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram. | Page 4, lines 25-26 – Figure 2 |
| | 16b | Cite studies that might appear to meet the inclusion criteria, but which were excluded and explain why they were excluded. | Page 4, lines 25-26 – Figure 2 |
| Study characteristics | 17 | Cite each included study and present its characteristics. | Page 5, line 6 - Table 2 |
| Risk of bias in studies | 18 | Present assessments of risk of bias for each included study. | Page 6, line 27 - Table 3 |
| Results of individual studies | 19 | For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimates and its precision (e.g., confidence/credible interval), ideally using structured tables or plots. | Page 6, line 27 - Table 3 |
| Results of syntheses | 20a | For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies. | Page 6, lines 10-26 |
| | 20b | Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g., confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect. | Page 6, line 27 - Table 3 |
| | 20c | Present results of all investigations of possible causes of heterogeneity among study results. | Not applicable |
| | 20d | Present results of all sensitivity analyses conducted to assess the robustness of the synthesised results. | Not applicable |
| Reporting biases | 21 | Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed. | Not applicable |
| Certainty of evidence | 22 | Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed. | Page 6, lines 10-26 |
| **Discussion** | | | |
| Discussion | 23a | Provide a general interpretation of the results in the context of other evidence. | Pages 8, lines 3-6 |
| | 3b | Discuss any limitations of the evidence included in the review. | Pages 8, lines 7-16 |
| | 23c | Discuss any limitations of the review processes used. | Page 6, lines 10-26; Page 13, lines 13-19 |
| | 23d | Discuss implications of the results for practice, policy, and future research. | Pages 8-13, lines 8-10 |
| **Other information** | | | |

| Section and Topic | Item # | Checklist item | Location where item is reported |
|---|---|---|---|
| Registration and protocol | 24a | Provide registration information for the review, including register name and registration number, or state that the review was not registered. | Not registered |
| | 24b | Indicate where the review protocol can be accessed, or state that a protocol was not prepared. | Not prepared |
| | 24c | Describe and explain any amendments to information provided at registration or in the protocol. | Not Applicable |
| Support | 25 | Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review. | Page 19, lines 9-14 |
| Competing interests | 26 | Declare any competing interests of review authors. | Page 14, lines 15-19 |
| Availability of data, code, and other materials | 27 | Report which of the following are publicly available and where they can be found template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review. | Pages 14-17, lines 21-24 |

## Annex 2: CIMMs Further Detailed Characterisation

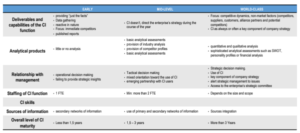
**Table 4.** Visualisation and Description of included CIMMs (developed by the authors)

<table>
<tr><th>Citation</th><th>CIMM Name</th><th>Visualisation</th><th>Description</th></tr>
<tr><td>(Calof, 1998)</td><td>Competitive Intelligence Quotient<br>(CIQ)</td><td>
<table>
<tr><th></th><th>Infancy</th><th></th><th>Level of maturity<br>Mature</th></tr>
<tr><td>Style</td><td>Ad hoc, reactive</td><td>⟷</td><td>Centralised tracking systems</td></tr>
<tr><td>Activities</td><td>Reading newspapers</td><td>⟷</td><td>Fully integrated, field research competitors, customers and suppliers</td></tr>
<tr><td>Resources</td><td>Librarian</td><td>⟷</td><td>CI department +</td></tr>
<tr><td>Tools</td><td>Profiles</td><td>⟷</td><td>CI systems, base lining</td></tr>
</table>
Source: Calof (1998, p. 4)</td><td>CI is about skills development, process, and structural and cultural change. The CIQ is the maturity level resulting from advancing style, activities, resources, and tools from infancy to maturity/World Class CI (WCCI). Building a competitive organisation requires its leaders' clear commitment and involvement, usually taking at least five years of committed effort from senior management to create a WCCI capability. A CI competencies list (from SCIP) is offered to support the development of the practice.</td></tr>
<tr><td>(Marceau & Sawka, 1999)</td><td>World-Class CI Program in Telecoms<br>(WCCIP-T)</td><td>
</td><td>The model presents five development planes as prerequisites and critical success factors to achieving a world-class CI: corporate culture (conducive to information sharing); straightforward interface (relationship and location of the CI within the organisation); relevance and extent of the CI portfolio of services; decision-making support (throughout the company); technical infrastructure (aggregation, organisation, and diffusion CI). The audience is the Telecom industry-leading global players, and critical stakeholders were the object of an interviews study for the development of the model.</td></tr>
<tr><td>(Prescott, 1999)</td><td>Action-Oriented CI Program<br>(AOCIP)</td><td>
Table 1
<table>
<tr><th colspan="5">Evolution of Competitive Intelligence</th></tr>
<tr><th>Time Period</th><th>Pre-1980</th><th>1980-1987</th><th>1988-Present</th><th>Future</th></tr>
<tr><td>Stages</td><td>Competitive Data Gathering</td><td>Industry and Competitor Analysis</td><td>Competitive Intelligence</td><td>Competitive Intelligence as a Core Capability</td></tr>
<tr><td>Key Defining Event</td><td>Porter's 1980 book, Competitive Strategy</td><td>The founding of the Society of Competitive Intelligence Professionals</td><td>The establishment of the Competitive Intelligence Review</td><td>CI courses taught in business schools across the world</td></tr>
<tr><td colspan="5">Attributes:</td></tr>
<tr><td>Degree of Formality</td><td>Informal</td><td>Emerging Formal Units</td><td>Formal</td><td>Integration of formal and informal</td></tr>
<tr><td>Orientation</td><td>Tactical</td><td>Tactical</td><td>Mixed</td><td>Strategic</td></tr>
<tr><td>Analysis</td><td>Little or none</td><td>Limited quantitative</td><td>Both quantitative and qualitative</td><td>Qualitative emphasis</td></tr>
<tr><td>Top Management Attention</td><td>Low</td><td>Limited</td><td>Moderate</td><td>High</td></tr>
<tr><td>Link to Decision-Making Processes</td><td>Little</td><td>Weak</td><td>Strong</td><td>Direct input</td></tr>
<tr><td colspan="5">Location:</td></tr>
<tr><td>Principle Location of CI Personnel</td><td>Library/Marketing</td><td>Planning/Marketing</td><td>Marketing/Planning/ CI Unit</td><td>CI Units/Marketing/Planning</td></tr>
<tr><td colspan="5">Key Issues:</td></tr>
<tr><td></td><td>Development of skills in information acquisition</td><td>Building a business case for CI<br>Spy image<br>Analytical skill development</td><td>Demonstrating bottom-line input<br>Demand vs. supply-driven CI<br>Counter-intelligence<br>International CI<br>CI Technology<br>Role of information technology</td><td>Managing the parallel process<br>Intelligence infrastructures for multinationals<br>CI as learning<br>Network analysis</td></tr>
</table></td><td>This model is based on the analysis of the evolution of CI to identify its key dimensions and levels. The dimensions and aspects (ten) are based on identified main attributes and the Key Decision Areas from the Decision-Oriented Approach to Designing a CI Program. The latter is based on the 1997 study on CI best practices from APQC. The main objective is to improve the effectiveness of CI while presenting a business case for proposal management professionals. The model adds additional value by identifying key defining events and issues in the evolution of CI.</td></tr>
<tr><td>(West, 2001)</td><td>CI Stages of Development<br>(CISoD)</td><td>
Table 1 The three stages of competitive development
<table>
<tr><th>Competitor</th><th>Data collection</th><th>Applications</th><th>Organisation</th><th>Systems for managing CI</th></tr>
<tr><td>Aware</td><td>Informal</td><td>Curiosity</td><td>None</td><td>None</td></tr>
<tr><td>Sensitive</td><td>Informal/ formal</td><td>Emulation</td><td>Marketing management information officer</td><td>Marketing information system</td></tr>
<tr><td>Intelligent</td><td>Formal</td><td>Anticipation</td><td>Competitive intelligence manager</td><td>Manual or computer-based CI systems</td></tr>
</table></td><td>The model assumes that organisations move through three stages of CI evolution across four dimensions: Data Collection, Applications, Organisation, and CI Systems. The model has three levels. First, Competitor Awareness - key competitors are known, some knowledge exists, the organisation rarely uses data for decision-making, and there is no CI Systems in place). Second, Competitor-sensitive - aware of competitive threats, relies exclusively on informal information flows, and there is still no structured intelligence program. Third, Competitor-intelligent - organisation anticipate competitive actions and events, dedicates serious resources, and has a specific location with the structure and systems to support the CI function. The model aims to understand the drivers and support the development of CI in Europe. The book offers further insight into the probability of using CI depending on the need for development capability and the ability to use it in practice.</td></tr>
</table>

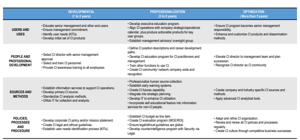
<table>
<tr><th>Citation</th><th>CIMM Name</th><th>Visualisation</th><th>Description</th></tr>
<tr><td>(APQC et al., 2004)</td><td>FIICH Model (FIICH)</td><td>
<table>
<tr><th>Prestart-up</th><th>Start-up</th><th>Established</th><th>World-Class</th></tr>
<tr><td>Knowledgeable CI personnel</td><td>Demonstration project</td><td>Developed IT used as an interactive tool</td><td>Embedded CI culture</td></tr>
<tr><td>Determined role of IT</td><td>Network design plan</td><td>Project-based CI</td><td>Dialogue-based CI</td></tr>
<tr><td>Promotional plan</td><td>Awareness training</td><td>Established product line</td><td>Integration of strategic and tactical intelligence</td></tr>
<tr><td>Identifiable champion</td><td>Developing IT platform</td><td>Consistent application of CI analytical framework</td><td>Direct role on key teams</td></tr>
<tr><td>Preliminary administrative structure</td><td>Ad hoc requests dominate</td><td>Coordination of all CI activities throughout the company</td><td>Simulations and modeling of competitive dynamics</td></tr>
<tr><td>Identifiable target of opportunity</td><td>KIT process to prioritize focus</td><td>Formalized evaluation process</td><td></td></tr>
<tr><td></td><td>Informal feedback</td><td>Network tuning of local champions</td><td></td></tr>
<tr><td></td><td>CI code of ethics</td><td>Knowledgeable and demanding CI users</td><td></td></tr>
</table>
NOTE: Bold activities are essential to be in a particular stage of development; italicized activities represent transition points</td><td>The development of a CI program (CIP) proceeds through four stages: prestart-up, start-up, established, and world-class. Each stage of development has an identifiable set of critical activities or indicators that allows a company to know its level and transition activities to the next stage of the CI program development. The model is based on the premise that CIPs can be characterised by their stage of development and that identified external and internal factors may cause reversals to earlier stages — if not the failure of the CIP – must be examined. The model offers a methodology to evolve across dimensions into more advanced stages: Focus (clear set of goals and objectives); Implement (organisational culture); Institutionalise (incorporate CI practices); Change (modify processes, behaviours, and performance); Hone (dynamic, evolving, continuously improving activity). This empirical study provides a comprehensive understanding of what it takes to have a successful CI functional unit. Based on years of research of leading-edge organisations – supported by examples of best practices and tips from actual practitioners — it intends to guide readers in their own CI efforts. The study also aims to influence the academic community in researching the role of an intelligence function in decision-making theory.</td></tr>
<tr><td>(J. P. Herring & Leavitt, 2011)</td><td>CI Maturity Matrix (CIMMx)</td><td>
<table>
<tr><th></th><th>Ad-Hoc</th><th>Emerging</th><th>Defined</th><th>Institutional</th><th>Optimized</th></tr>
<tr><td>Teams</td><td>• Individuals perform CI occasionally and incon-sistently.</td><td>• Identified people doing CI part-time in business units and Shared Services.</td><td>• Full-time CI teams supported by annual budgets.<br>• Defined CI skills, job description, roles and responsibilities.</td><td>• Senior leader as enterprise CI champion.<br>• Formal, full-time CI teams across enterprise with strong internal intelligence networks.</td><td>• Strong support for enterprise CI from CEO and senior leadership.<br>• CI Network supports enterprise strategic and tactical intelligence.<br>• Frequent dialogue with and input from senior leaders.</td></tr>
<tr><td>Tools</td><td>• Some scattered commercial databases in the enterprise.</td><td>• Central commercial database support.</td><td>• Enterprise CI portal for access to commercial databases.</td><td>• Standard set of CI templates defined and in use.<br>• Central CI repository for CI artifacts and internal databases.<br>• Formalized CI training (basic, trade show, ethics, etc.)</td><td>• Advanced CI training (analysis techniques, counter-intelligence)<br>• Web-based CI analytical tools</td></tr>
<tr><td>Techniques</td><td>• Secondary sources.</td><td>• Primary and secondary sources.</td><td>• KITS/PIRs solicited regularly.<br>• SWOT, 5 Forces analysis.</td><td>• Analysis and impact part of all CI products.<br>• War-gaming, scenario planning regularly applied.</td><td>• Numerous analytical techniques used, with future orientation – simulations and modeling.</td></tr>
<tr><td>Processes</td><td>• Data gathering.</td><td>• CI Process Cycle understood and applied.</td><td>• Established CI ethical and legal guidelines.<br>• Documented CI processes.<br>• CI Teams involved in CI best practice organizations.</td><td>• Enterprise-level CI program branded, promoted and aligned with business goals.<br>• Methods to demonstrate ROI of CI determined.<br>• CI integral to strategic plans and business decisions.</td><td>• Enterprise-wide knowledge-sharing with "Culture of CI" in place.<br>• Push-pull demand for intelligence products with substantial re-use as a way of doing business.</td></tr>
<tr><td>Products</td><td>• Newsletters.<br>• Ad hoc memos, reports pushed upwards.</td><td>• Newsletters.<br>• Competitor profiles.<br>• Market assessments.<br>• Personality profiles.</td><td>• Newsletters.<br>• Competitor profiles.<br>• Market and competitor<br>• Analyses.</td><td>• Newsletters include analyses and implications<br>• Established and scheduled CI products packaged and pushed to decision makers.</td><td>• Forward-looking newsletters with insights and implications.<br>• Scheduled CI products include business implications.</td></tr>
</table></td><td>The matrix is based on a six-month study of the core of the entire value chain processes to optimise the CI of the enterprise. A later benchmark in best practices determined that it was ineffective to continue to be 'everything to all people.' Consequently, the group re-assessed its ion and audience and focused primarily on providing CI to support enterprise-wide strategic decisions and research new market potential. As a result, the author developed the CI Maturity Matrix in early 2006 to serve as a roadmap to achieve a CI process that provided more value to the enterprise. The matrix is five stages per five dimensions description of best practices to develop mature CI practices.</td></tr>
<tr><td>(Comai & Prescott, 2007)</td><td>World Class CI (WCCI)</td><td>
</td><td>The structure of the WCCI model identified nine dimensions subdivided into 48 aspects. The authors prepared a statement describing what the judges believe to be a world-class performance for each dimension and its accompanying aspects. The modes were defined so that their statements apply regardless of how the Cl function is organised in the Strategic Business Unit (SBU). The authors defined "world-class" not as "the best that currently exists" but as "the ultimate best that might be achieved". The nine dimensions are: 1) Strategic Significance (recognised importance of Cl defining the scope and level of Cl activities); 2) CI in the Organisational Structure (clear operational vision between CI & the SBU); 3) CI Culture (organisational culture allows CI contribution to be maximised); 4) & 5) People and Physical resources (necessary for CI effective functioning); 6) CI Process (clearly defined and well established for gathering, validating, analysing, and storing CI); 7) CI project management (systems in place for selecting and prioritising CI projects); 8) Management Control (clear processes in place for top-level management control of Cl operations); 9) Evolution Of The CI Unit (clearly defined evolutionary strategy for how the Cl vision is to be achieved). The measurement scale to identify the development level is 1) We have not started this yet. 2) We have made some progress but still have a long way to go; 3) We have achieved a lot but still have a lot to do. 4) We have nearly achieved this but still have some work to do; 5) We have fully achieved this. The study aims to answer four research questions: What are the dimensions? What are the main dimensions? What are the milestones and relationships between them? What are the best ways to achieve WCCI?</td></tr>
</table>

| Citation | CIMM Name | Visualisation | Description |
|---|---|---|---|
| (Singh et al., 2008) | Roadmap for Enduring CI Success (RECIS) |  | The RECIS results from the evolution of two reports and a study to ensure the success of CI activities in an organisation. The Self-Diagnostic Framework (SDF) (Singh & Beurgschens, 2006) provides value by describing the current stage of your program's development per attribute (dimension). The column with the most checks is where the organisation is in terms of CI development level (stage). This tool is a starting point to begin the analysis of the CI capabilities of an organisation by determining at which level it is and defining how it can be improved. The survey and white paper from Fuld & Singh (2007) explored the critical success factors of CI Programs (CIPs) across the globe. Using the exact eleven dimensions and "Four Intelligence Stages" from the SDF, it developed a more scientific and more profound assessment of the state of the CI discipline. A roadmap emerged from the two-year study where 141 worldwide companies examined and assessed their intelligence efforts (Fuld & Singh, 2007). Capability attributes are the key building blocks to developing a fully operational intelligence and competent CI function capability. The phases of development are the milestones for developing your function. The aim is to accelerate CI improvement as an individual, a team, or a function.<br>NOTE: This study was based on a self-assessment test submitted via a web survey. Fuld & Company did not interview or audit each respondent after submitting the survey. |

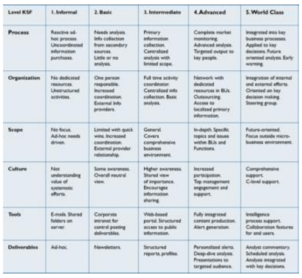
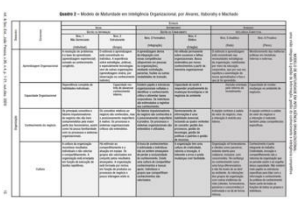
| Stages | | | | |
|---|---|---|---|---|
| Attributes | Stick Fetching | Pilot | Proficient | World Class |
| 1. Roles and responsibilities | Undefined role, with arbitrary, unstructured responsibility and focus | Evolving from conflicting roles to focused direction from an executive sponsor | Defined roles and responsibilities that are understood by the CI team | Agreed service level agreement between the CI team and executive management team |
| 2. Processes | Top-down, one-way chain of requests | Introduction to KITs, bespoke, piecemeal, steep learning curve for CI stakeholders and contributors | KITs aligned to a wider executive management audience | CI embedded to such an extent that intelligence dialogue drives all major decisions |
| 3. Secondary research | Web as the sole source of intelligence | Exploring and trying additional external sources | Tap into internal secondary sources | Fully integrated use of internal and external electronic and grey literature sources |
| 4. Primary research | Nil | Recognize the value of human sources but issues with obtaining timely intelligence | Use of 'friendly' human network to access meaningful targeted intelligence | Fully integrated use of internal and external human sources |
| 5. Analysis | Nil | Occasional use of basic analytical tools | Use of more analytical tools | Selection and use of advanced analytical tools |
| 6. People | No formal CI staff. Volunteering 'information' provision | Individuals nominated by sponsor | Trained CI practitioners working to agreed legal and ethical guidelines | Experienced CI practitioners |
| 7. Organizational structure | CI absent from the organizational chart | CI nominees not yet recognized in the corporate hierarchy | Placement of CI team(s) in appropriate part(s) of the organization | Team(s) optimally placed across multiple parts of the organization |
| 8. CI awareness | Limited to a handful of individuals and driven by curiosity | Increased awareness is triggered by a 'Pearl Harbor' in the competitive environment | Increased awareness by a sustained communications campaign | CI embedded in job description, performance appraisals, induction programs and meetings |
| 9. Technology | Overreliant on desktop Internet searching | Recognition that technology is not a substitute for to actionable intelligence; determining its role | Trying appropriate technology and integration with existing platforms | Fully developed technology complements human systems |
| 10. Value perception | Limited or no recognition | Driven by a recognition that CI is necessary | Formal justification of the value of the CI capability. Formalized evaluation process | Conviction that decisions cannot be made without actionable intelligence |
| 11. CI professionalism | Nil | Nil/limited | Increased need for professional development | Management plan for CI team's career progression |

| Citation | CIMM Name | Visualisation | Description |
|---|---|---|---|
| (Heppes & Du Toit, 2009) | CI Function Maturity Level (CIFML) |  | Heppes identified the typical evolution of a world-class CI capability typically as spanning three significant stages; 1) Early-stage (providing facts and creating CI awareness \| less than 1,5 years of operation); 2) Mid-level capability (identifying trends and implications from gathered data, within an emerging partnership with CI users \| operational between 1,5 - 3 years); 3) World-class (CI regarded as a key component of company strategy \| more than three operating years). These stages evolve across seven dimensions: 1) CI Function (CIF) deliverables and capabilities; 2) analytical products; 3) Relationship with management; 4) staffing of CI function; 5) CI skills; 6) sources of information. The overall aim is to establish the level of maturity of the CI function. This study focused on identifying the maturity level of CI for a South African retail bank. |

| | EARLY | MID-LEVEL | WORLD-CLASS |
|---|---|---|---|
| Deliverables and capabilities of the CI function | • providing "just the facts"<br>• Data gathering<br>• reactive in nature<br>• Focus: immediate competitors<br>• published reports | • CI doesn't, direct the enterprise's strategy during the course of the year | • Focus: competitive dynamics, non-market factors (competitors, suppliers, customers, alliance partners and potential competitors)<br>• CI as always or often a key component of company strategy |
| Analytical products | • little or no analysis | • basic analytical assessments<br>• provision of industry analysis<br>• provision of competitor profiles<br>• basic analytical assessments | • quantitative and qualitative analysis<br>• sophisticated analytical assessments such as SWOT, personality profiles or financial analysis |
| Relationship with management | • operational decision making<br>• failing to provide strategic insights | • Tactical decision making<br>• mixed orientation toward the use of CI<br>• emerging partnership with CI users | • Strategic decision making.<br>• Use of CI<br>• key component of company strategy<br>• alert strategic management to issues<br>• Access to the enterprise's strategic committee |
| Staffing of CI function | • 1 FTE | • Min: more than 2 FTE | • Depends on the size and scope |
| CI skills | | | |
| Sources of information | • secondary networks of information | • use of primary and secondary networks of information | • Sources integration |
| Overall level of CI maturity | • Less than 1,5 years | • 1,5 – 3 years | • More than 3 Years |

| Citation | CIMM Name | Visualisation | Description |
|---|---|---|---|
| (J. P. Herring & Leavitt, 2011) | World-Class CI Program Roadmap (WCCIPR) |  | The roadmap shows where the CI Program (CIP) is now, the vision of where the organisation wants it to be, and the steps needed to get there. The roadmap organises a CIP in three-time stages: 1) developmental (first 1-2 years), 2) professionalisation (3-5 years), and 3) optimisation (6+ years). The Developmental Stage is critical to building a world-class professional program (WCCIP) from the onset. All dimensions must be identified and put in place over the first two years to develop a strong foundation. The Professionalisation Stage requires formidable effort to enhance the collection and analysis methods while advancing intelligence policies and procedures requires experienced intelligence expertise. Once these essential functions and processes are established, the next set of tasks is to professionalise those operations and the individuals who produce and apply the intelligence. The Optimisation Stage is the final stage in becoming a WCCIP. The real challenge is to maintain the level of organisational performance for years afterwards. The SCIP-IRI study found that the average age of world-class programs was about eight years. The vertical axis contains the four functional dimensions that form the core of all CI programs: 1) users and uses; 2) people and their professional development; 3) sources and methods; 4) the policies, processes, and procedures that bring the program altogether and ensure it runs smoothly. Following is a descriptive discussion of the twelve boxes on the Herring-Leavitt World-Class CI Program Roadmap. The choice of a roadmap framework for the WCCI model shows the evolution of the world-class process over time and, most significantly, promotes organisational learning. |

| | DEVELOPMENTAL (1 to 2 years) | PROFESSIONALIZATION (3 to 5 years) | OPTIMIZATION ( More than 5 years) |
|---|---|---|---|
| USERS AND USES | • Educate senior management and other end-users.<br>• Ensure management commitment.<br>• Identify user needs (KITs).<br>• Develop initial set of CI products | • Develop executive education program.<br>• Align CI operations with company strategic/operational calendar, plus produce actionable products for key user groups.<br>• Establish management advisory/ oversight group. | • Ensure CI program becomes senior management responsibility.<br>• Enhance and customize CI products and dissemination methods. |
| PEOPLE AND PROFESSIONAL DEVELOPMENT | • Select CI director with senior management approval.<br>• Select and train CI personnel.<br>• Provide CI awareness training to all employees. | • Define CI position descriptions and career development paths.<br>• Develop CI education program for CI practitioners and management.<br>• Train other functions to use CI.<br>• Create CI community/ network company-wide and recognition. | • Elevate CI director to management team and plan succession.<br>• Recognize CI director as CI community |
| SOURCES AND METHODS | • Establish information services to support CI operations.<br>• Develop primary CI source.<br>• Standardize CI analysis methods.<br>• Utilize IT for collection and analysis. | • Professionalize human source collection.<br>• Establish early warning systems.<br>• Create CI futures capability.<br>• Integrate into strategic planning.<br>• Develop IT to enhance CI utilization.<br>• Incorporate self-educational feature into information services for non-CI people. | • Create company and industry specific CI sources and methods.<br>• Apply advanced CI analytical tools. |
| POLICIES, PROCESSES AND PROCEDURE | • Develop corporate CI policy and/or mission statement.<br>• Create CI legal and ethical guidelines.<br>• Establish user-needs identification process (KITs). | • Establish CI budget as line item.<br>• Create CI evaluation program (MOE/ROI).<br>• Ensure legal/ethical guidelines are global.<br>• Develop counterintelligence program with Security via Legal. | • Adapt and refine CI organization.<br>• Review and renew all CI policies and processes regularly.<br>• Create CI culture through competitive business successes. |

| Citation | CIMM Name | Visualisation | Description |
|---|---|---|---|
| (Hedin et al., 2014) | World Class MI Roadmap (WCMIR) |  | The World Class Market Intelligence Roadmap (WCMIR) incorporates intelligence development into an evolutionary process. The authors identified five levels of growth from the start to the world-class level and six key success factors (KSF) that move the program through those growth levels. The role of the CI manager is different for each of the five levels of the intelligence evolution roadmap. The same applies to all six Key Success Factors (KSF): the further the program advances through the various levels, the more sophisticated process it needs. Combining the six KSFs with the five stages creates a 30-box matrix. Each box describes a KSF relevant to each of the development steps. To grow the CI function, organisations need to implement the appropriate measures. Reviewing the development roadmap, one can identify the present status and what is necessary to move CI up a level. The roadmap can also help determine the CI function's future objectives. Over time, most CI functions should reach the intermediate level, where the basic intelligence processes are in place. However, several specific issues arise at that level and must be addressed before the organisation can move toward the advanced and world-class levels. The framework is based on research conducted during 2005- 2008 with 700 companies, and their input has been used to verify the roadmap concept. In addition, many companies have empirically tested the concept. |
| (Oubrich et al., 2018) | Competitive Intelligence Maturity Model (CIMM-M) |  | The maturity model proposed is based on a comprehensive review of recent literature. The objectives of this study are threefold: 1) determine the significant purposes of a CIMM, 2) identify the CI dimensions and levels of maturity, and 3) evaluate Moroccan CI practices. The conceptual framework articulates the CI dimensions and three maturity levels. The six CI dimensions are CI Culture; CI deliverables; CI sourcing; CI cycle; CI investment in resources; CI users; and CI application). Implementing these dimensions determines the position across three levels: early, mid, and world-class. The model was tested through an empirical study conducted in the Moroccan context. The results show that most Moroccan companies are in the early stage of CI, using environment scanning in a not-so-intense competitive environment allowing for the absence of a CI structure. However, most of these Moroccan companies are not able to cope with changes in the business environment as CI systems and processes are implemented on an irregular basis. |
| (M-Brain et al., 2019) | M-Brain - World-Class Intelligence Framework<br>(WCIF) |  | M-Brain´s Intelligence Framework (M-BIF) expands the Hedin et al. WCMIR to help organisations achieve three benefits: better and faster decisions, time and cost savings, and organisational learning and new ideas. This is achieved by a systematic strategic market and competitive intelligence operation. Results are measured against and plotted on the matrix of nine Key Success Factors of an intelligence organisation (KSF) against five increasing levels of CI professionalism. The M-BIF framework distinguishes five maturity levels from Level 1 - beginners or "firefighters" - to the most advanced Level 5, the "futurists" and World Class intelligence organisations. The supporting survey gives the international CI community a good picture of the global average and world-class intelligence functions. In addition, the results offer in-depth information about the size of intelligence teams, their place within the organisation, available budget, number of stakeholders and contributors to intelligence (for co-creation) and much more. In concrete terms, the survey results are used by many companies to benchmark, set aspirational goals and develop roadmaps with implementation plans. |
| (Alvares et al., 2020) | Organisational Intelligence Maturity Model (OIMM) |  | The Organisational Intelligence Maturity Model (OIMM) presents the condition of dependence between information management (IM), knowledge management (KM), and CI to demonstrate that IM and KM are associated with the CI maturity level. The results from exploratory qualitative research based on a literature review show that IM is the foundation for KM, which, in its turn, supports and enables CI. This confirms that the maturity level as a series of one-dimensional linear stages is also applicable to the organisational intelligence expanded model. The result is a matrix of 2 categories and 17 dimensions across the three stages (IM, KM, and CI) and six |

| Level KSF | 1. Informal | 2. Basic | 3. Intermediate | 4. Advanced | 5. World Class |
|---|---|---|---|---|---|
| Process | Reactive ad-hoc process. Uncoordinated information purchases. | Needs analysis. Info collection from secondary sources. Little or no analysis. | Primary information collection. Centralized analysis with limited scope. | Complete market monitoring. Advanced analysis. Targeted output to key people. | Integrated into key business processes. Applied to key decisions. Future oriented analysis. Early warning. |
| Organization | No dedicated resources. Unstructured activities. | One person responsible. Increased coordination. External Info providers. | Full time activity coordinator. Centralized info collection. Basic analysis. | Network with dedicated resources in BUs. Outsourcing. Access to localized primary information. | Integration of internal and external efforts. Oriented on key decision making. Steering group. |
| Scope | No focus. Ad-hoc needs driven. | Limited with quick wins. Increased coordination. External provider relationship. | General. Covers comprehensive business environment. | In-depth. Specific topics and issues within BUs and Functions. | Future-oriented. Focus outside micro-business environment. |
| Culture | Not understanding value of systematic efforts. | Some awareness. Overall neutral view. | Higher awareness. Shared view of importance. Encourages information sharing. | Increased participation. Top management engagement and support. | Comprehensive support. C-level support. |
| Tools | E-mails. Shared folders on server. | Corporate intranet for central posting deliverables. | Web-based portal. Structured access to public information. | Fully integrated content production. Alert generation. | Intelligence process support. Collaboration features for end users. |
| Deliverables | Ad-hoc. | Newsletters. | Structured reports, profiles. | Personalized alerts. Deep-dive analysis. Presentations to targeted audience. | Analyst commentary. Scheduled analysis. Analysis integrated with key decisions. |

| CI dimension | Early stage CI | Mid-level CI capability | World-class CI capability |
|---|---|---|---|
| CI Strategy and Culture | - The competition in the business environment is not intense<br>- CI practice is only about environment scanning<br>- Absence of CI structure<br>- Not able to cope with changes in the business environment | - The competition in the business environment is intense<br>- CI practices are about environment scanning and asset protection<br>- Absence of CI structure<br>- Able to cope with changes in the business environment | The competition in the business environment is very intense<br>- CI practices are about environment scanning, asset protection, and influence<br>- Existence of CI structure<br>- Able to drive the change in the business environment |
| CI Relationship with Management | CI output is used by marketing or sale and commercial departments | CI output is used by export department | CI output is used by top management or strategy department |
| CI Structure | - The age of a CI unit within organization is between 0-5 years<br>- Scanning environment activity exists<br>- CI team has less education (most with less than bachelor degree) and less years of experience | - The age of CI unit within organization is between 6-10 years<br>- Scanning environment and protection asset activities exist<br>- CI team is composed of people who have bachelor's degrees and fewer years of experience | - Environment scanning, assets protection, and influence activities in existence for more than 10 years<br>- CI team has advanced degrees (mainly masters or PhD) and several years of experience |
| CI Resources | CI human resources have less education (most with less than bachelor degree), often lower-level managers | CI human resources are composed of people who have bachelor's degrees, often senior/middle managers | CI human resources are composed of people who have masters or PhD degrees, often top managers |
| CI System | Few information gathering sources utilized annually | Several information gathering sources utilized monthly | Several information gathering sources utilized daily |
| CI Deliverables and Capabilities | The CI process output released annually | The CI process output released monthly | The CI process output released daily |
| CI Analytical Products and CI Use | Few analytical product methods and CI deliverables utilized annually | Several analytical product methods and CI deliverables utilized monthly | Several analytical product methods and CI deliverables utilized daily |
| CI Impact | CI impacts operational side of an organization, mainly protection of their assets, coordination of their activities, information about the change in the environment. | CI impacts tactical side of an organization, mainly access to new markets, coordination of their strategies. | CI impacts strategic side of an organization, mainly allowing companies to make better decisions, create new knowledge on their products, services and processes. |

| Citation | CIMM Name | Visualisation | Description |
|---|---|---|---|
| | | | levels (Non-Managed/Individual, Structuring/Group, Formative/Integration, Effective/Creation, Analytical/Network, and Proactive/Full). The study aims to explain business development relative to the progression from IM to KM and CI maturity levels to understand, implement, improve, benchmark or self-assess IM, KM, or CI models. |

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Stevan Didijer
1911-2004

# SWOT analysis problems and solutions: Practitioners' feedback into the ongoing academic debate

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**ABSTRACT** The literature on SWOT is characterized by a debate among academics who have identified problems and proposed solutions for the strategic management tool, yet little research to date has captured practitioners' perspectives. Recent literature indicates that SWOT is still the most popular strategic management tool among competitive intelligence (CI) professionals. The purpose of this study is to bridge this academic-practitioner divide in the SWOT literature by conducting a cross-sectional survey that gathers practitioners' feedback regarding whether they are experiencing the problems or employing the solutions proposed by academia. A survey was distributed via LinkedIn to collect data from CI and other business professionals who conduct SWOT in the workforce. The findings confirm that practitioners experience select problems identified by the literature. Specifically, they may have too many factors per SWOT category, may be defining factors with ambiguous and unclear words, and may not have a means for resolving conflicts when factors fall in multiple categories (e.g., opportunity and threat). The findings also indicate that practitioners may not be consistently conducting SWOT as a structured business process, as proposed in the literature. The feedback provided by CI and other business professionals aids in closing the academic-practitioner divide by more clearly identifying persistent issues with SWOT and creating valuable and actionable insights that will drive the continual improvement of this popular strategic management tool.

**KEYWORDS**: academic-practitioner divide, strategic management tools, SWOT

## 1. INTRODUCTION

The evolution of globalization and the ever-changing dynamics of digital technologies continue to disrupt established industry business models. For business leaders navigating an exceedingly volatile environment, maintaining a sustainable

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competitive advantage requires innovative organizational processes in strategic management. Specifically, these processes must deliver actionable intelligence on the macro-environmental forces driving disruption and reinforce an acute awareness of internal resources and capabilities. Empowered by these innovative processes, business leaders may be better equipped to develop strategies that ensure survival and success in an evolving industry landscape.

Academia has introduced an array of strategic management tools to support business leaders in the development of such strategies with SWOT (Strengths, Weakness, Opportunities, Threats) analysis being one of the prevalent fixtures in MBA programs. The pervasiveness of SWOT analysis has manifested in practice as this methodology is used by practitioners more often than any other strategic management tool (Frost, 2003; Qehaja, et al., 2017). This finding was further validated by a survey of CI professionals that confirmed SWOT as their primary strategy tool (Author & Hoffman, 2023). Furthermore, the number of articles published on SWOT in peer-review journals has continued to increase over six decades (Ghazinoory, et al., 2011; Gürel & Tat, 2017; Helms & Nixon, 2010), indicating a steadfast and growing interest in SWOT among academics. Yet, amidst its popularity in practice and in literature, there remains an ongoing debate surrounding the fundamental value of employing SWOT for strategy development.

At the core of the debate is SWOT's methodological process and whether it can provide any value for strategy development. On the one side, academics dismiss the utility of SWOT due to inherent problems with the methodology; on the other side, academics have proposed solutions designed to salvage valuable insights (Gürel & Tat, 2017). While academics from both schools of thought have weighed in, little research to date has considered the practitioners' perspective. Empirical research is lacking regarding practitioners' experiences with the alleged problems of the methodology or in what conditions SWOT is actually being used. The gap between proposed SWOT research by academia and lack of practitioner feedback epitomizes an academic-practitioner divide. In order to bridge the divide, academics must elevate the level of managerial relevance by inviting the practitioners' perspective into the debate. According to Jaworski (2011), managerial relevance is the degree to which practitioners perceive academic research as supporting their work because the findings are important, actionable, and meaningful. The present research aims to elevate the managerial relevance regarding SWOT by addressing three key research questions:

- What are the fundamental problems with SWOT as identified in the literature and do practitioners experience these problems in practice?
- What are the best conditions for conducting SWOT as proposed in the literature and do practitioners conduct SWOT in these conditions?
- What are the current challenges that practitioners experience with SWOT and what can researchers learn from their feedback to improve the methodology?

Addressing these research questions will begin with a literature review that evaluates two bodies of literature in strategic management theory. The first comes from the resource-based view that serves as the foundation for assessing internal strengths and weaknesses. The second consists of the dynamic capabilities framework, which provides the foundation for identifying external opportunities and threats. From there, studies will be discussed that identify problems and propose ideal conditions for SWOT; thereby forming the hypotheses. The methodology section will discuss the survey development and distribution to practitioners, followed by a discussion of results, limitations, and future research opportunities.

## 2. LITERATURE REVIEW

A review of the literature provided insight into the origins of SWOT and how its comprehensive approach to strategy has helped it persevere for more than half a century. Although the earliest origins can be traced back to the 1950's and 1960's, Weihrich (1982) was the first to introduce SWOT as a strategic management tool (Ghazinoory, et al., 2011). Weihrich originally proposed SWOT as a key part of the strategic planning process through which practitioners conducted an audit of internal resources (i.e., strengths and weaknesses), scanned for potentially disruptive factors in the macro-environment (i.e., opportunities and threats), and analyzed these variables in a matrix designed to facilitate strategy development. Decades later, SWOT is used more frequently than any other strategic management tool (Frost, 2003; Qehaja, et al., 2017) and remained uniquely capable of fulfilling a critical step in the strategic management process (Gürel & Tat, 2017). The unique capabilities of SWOT can be tied to its holistic approach to strategy, which by focusing on internal resources and external forces aligns with strategic theory from two parallel schools of thought: the resource-based view and the dynamics capabilities framework.

### 2.1. The resource-based view

The resource-based view (RBV) looks explicitly at internal resources within the organization (Kraaijenbrink, et al., 2009). According to the RBV, the fundamental strategic imperative of an organization is to acquire and control those resources that are valuable, rare, imperfectly mobile, inimitable, and non-substitutable to achieve competitive advantage (Hunt & Derozier, 2004). By focusing the strategic planning process internally, the RBV aligns with the process of auditing internal resources (i.e., strengths and weaknesses) in SWOT.

Valentin (2001) was among the first academics to bring SWOT and the RBV school of thought together in the literature. According to Valentin, an RBV approach complemented SWOT by perceiving the organization as a collection of resources that operates in a larger environment with threats and opportunities. Clardy (2013) built on the work of Valentin by demonstrating how an RBV approach to SWOT presented three strategic actions: to invest to make strengths stronger, to take action to mitigate weaknesses, and to use strengths to capture opportunities. In this way, conducting SWOT from a RBV conceptualized the situational assessment so that an organization can employ internal resources (i.e., strengths and weaknesses) in response to external forces (i.e., opportunities and threats) in the environment to achieve a competitive advantage.

### 2.2. The dynamic capabilities framework

The dynamic capabilities framework (DCF) addressed the process of scanning for potentially disruptive forces in the macro-environment (i.e., opportunities and threats). According to the framework, the fundamental strategic imperative of an organization was to identify the likely trajectory of technology and the market and to acquire the necessary resources to maintain or achieve competitive advantage (Kay, et al., 2018). Teece (2007) called for a function within the organization such as a CI team to look externally, recognize macro-environmental trends, then direct and redirect resources in the organization in response to these trends. By focusing the strategic planning process externally, the DCF aligned with the practice of scanning the macro-environment for potentially disruptive forces in a SWOT.

The DCF is among the latest iterations of external models for strategy, but has yet to be tied to SWOT in the literature. According to Kay et al., (2018), the DCF was based on previous external models like the Five Forces framework (Porter, 1980). DCF expanded Porter's research by demonstrating how scanning the macro-environment can present strategic choices like seizing opportunities, acquiring necessary resources, or reconfiguring assets to achieve competitiveness (Teece, 2007). With foundational skills in research, analysis, and communication, analysts on a CI team are well-positioned to serve in this capacity by scanning the macro-environment, analyzing key trends, and communicating findings to leadership who can then make informed decisions to maintain and achieve competitiveness (Author & Hoffman, 2003). Although not yet tied to SWOT, scanning the macro-environment with a dynamic capabilities function like a CI team aligns with the process of identifying disruptive forces (i.e., opportunities and threats) so that an organization can reconfigure or acquire resources (i.e., strengths and weaknesses) to achieve competitive advantage.

## 2.4. Problems with SWOT

In a meta-analysis of SWOT research, Ghazinoory et al., (2011) credited Hill and Westbrook (1997) for making important contributions to the methodological development by identifying a comprehensive list of problems. For this reason, the present research references Hill and Westbrook to test the issues practitioners may be experiencing. In their seminal study (cited over 1,500 times), Hill and Westbrook reviewed the SWOT process at over 50 organizations and recognized seven problems that practitioners may experience when using the methodology. These problems identified by Hill and Westbrook were ultimately used to develop the hypotheses for the study (Table 1).

**Table 1.** Hypotheses drawn from problems with SWOT as identified by Hill and Westbrook (1997).

| | |
|---|---|
| H1. | Practitioners are experiencing the problems identified by Hill and Westbrook (1997) while conducting SWOT. |
| $H1_a$ | Practitioners do not verify factors with primary data. |
| $H1_b$ | Practitioners do not verify factors with secondary data. |
| $H1_c$ | Practitioners do not verify factors with analyses. |
| $H1_d$ | Practitioners have no means of limiting the number of factors generated. |
| $H1_e$ | Practitioners have no means of prioritizing factors. |
| $H1_f$ | Practitioners are defining factors with unclear terms. |
| $H1_g$ | Practitioners are defining factors with ambiguous terms. |
| $H1_h$ | Practitioners have no means of resolving conflicts. |
| $H1_i$ | Practitioners are experiencing a problem because there is no logical link to implementation. |
| $H1_j$ | Practitioners are experiencing a problem because only a single level of analysis is required. |

The first problem identified was the lack of obligation to verify factors (i.e., strength, weakness, opportunity, or threat) with data or analyses; meaning practitioners may generate factors that are liable to subjectivity without analytic rigor. Hill and Westbrook (1997) also observed that there were no limits on the number of factors to be considered and no means of prioritizing factors in a SWOT. This can create confusion and reduce the degree to which factors are relevant to the organization. Other problems that could contribute to confusion included unclear or ambiguous definition of terms and no means of resolving conflicts such as during the placement of factors (e.g., whether a factor is a strength or weakness). Finally, Hill and Westbrook argued that there was no logical link to implementation and only a single level of analysis is required, resulting in practitioners squandering the valuable insights that SWOT can provide.

## 2.5. Proposed conditions for conducting SWOT

In addition, this study addressed the optimal conditions for conducting SWOT proposed in the literature. At the conclusion of the same meta-analysis, Ghazinoory, et al., (2011) considered the previously mentioned problems and offered a model for the best conditions to conduct SWOT. Specifically, Ghazinoory, et al., suggested that the best conditions for the analysis are within a structured business process and within a stable market environment. More broadly, these conditions can be described by a two-by-two matrix in which the degree of structure around the business process is defined along the Y-axis and the degree of stability in the market environment is defined along the X-axis (Figure 1).

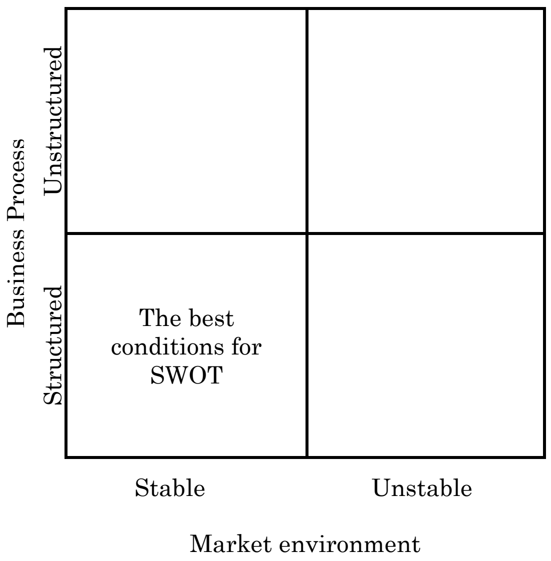


**Figure 1**. Best conditions for conducting a SWOT, modified based on model by Ghazinoory, et. al., (2011).

Since these conditions were proposed in a meta-analysis and not empirically tested, this research aimed to test these conditions among practitioners for the first time. To test the extent to which a business process is structured, this study drew from empirical research in computer science that tested how well different modeling languages represent structured versus unstructured business processes (Cardoso, et al., 2016). In order to apply this research to SWOT, the present study tested the degree to which SWOT was predictable and repetitive among practitioners according to the four types of business processes defined by Cardoso, et al., and adapted from Reichert and Weber (2012). Specifically, this study sought to understand whether practitioners conducted SWOT by:

1) following the same steps sequentially every time,
2) following the same steps generally but may go back to a previous step or skip a step,
3) following the steps loosely and in no particular order, or
4) conducting SWOT with unique steps and in a unique order each time.

Another optimal condition put forth in Ghazinoory, et al., (2011) requires that SWOT be conducted in a stable market environment. In the financial literature, a stable economy and market are usually defined as “facilitating (rather than impeding) the performance of an economy” (Schinasi, 2004, p. 8). In the absence of macro-economic shocks like the coronavirus pandemic, there are typically four indicators of a stable market environment that facilitate the performance of the U.S. economy: low unemployment numbers, low inflation, high consumer activity, and high investor activity (Jareño & Negrut, 2016). In order to test the long-term trends of these economic indicators in absence of macro-economic shocks, this study used descriptive statistics to identify the median unemployment rate (U.S. Bureau of Labor Statistics), personal consumption expenditures and gross private domestic investment (U.S. Bureau of Economic Analysis), and inflation of consumer prices in the U.S. (World Bank) for the last decade for which data is publicly available, specifically between January 2011 and January 2021.

Based on a review of the literature, the following hypotheses were developed to test for the first time whether practitioners are conducting SWOT in the optimal conditions as proposed by Ghazinoory, et al., (Table 2).

**Table 2.** Hypotheses drawn from best conditions for conducting SWOT as proposed by Ghazinoory, et al., (2011).

| | |
|---|---|
| H2. | Practitioners are conducting SWOT in the best conditions as proposed by Ghazinoory, et. al., (2011). |
| $H2_a$ | Practitioners are conducting SWOT as a structured business process. |
| $H2_b$ | Practitioners are conducting SWOT in a stable market environment. |

## 3. METHODOLOGY

As one of the first empirical studies to gather practitioner feedback on SWOT, the problems identified and ideal conditions proposed in the literature served as the foundation of the survey. Questions were developed using the guidelines of being relevant and meaningful, unambiguous, and easy to answer from the perspective of the participant (Connell, et al., 2018). A pre-test of the survey was conducted with business professors who had both taught SWOT as well as conducted SWOT as a practitioner.

Additionally, business and CI professionals who have conducted SWOT participated in the pre-test.

For valid inferences from survey data, respondents' characteristics must reflect the target population (Maholtra, 2019). To achieve this, a cross-sectional survey was distributed on LinkedIn using eleven groups whose title contained the term strategy or intelligence (e.g., Strategic Planning Society, The Strategic Management Society, Strategic and Competitive Intelligence Professionals). Professionals in the intelligence field were considered particularly relevant as they are highly focused on supporting executive level leaders in making more effective strategic decisions (Wheaton & Beerbower, 2006). To ensure respondents fit the sampling frame, the LinkedIn post requested practitioners to participate only if they had conducted SWOT at their organization.

Upon completion of the six-week collection period, the survey had a total of 41 participants and a 100% completion rate. Although limited, this does reflect the trend of declining response rates for organizational research (Fulton, 2016). Fulton argued that non-response is a growing issue and noted that "if there are no systematic differences between respondents and non-respondents, then the sample remains representative of the population and can provide valid inferences" (p. 4). Taking into account that respondents were both affiliated with strategic management organizations and conducted a SWOT at their organization, the sample size was deemed acceptable for this pilot study.

In the respondent pool, 40% identified as Executives and 33% as Managers, while Analysts reflected 28% of the group. Considering SWOT is a strategic management tool and Managers and Executives accounted for almost two-thirds of the participants, the position levels were deemed well represented. There was a representative distribution of responses related to company size in terms of employees: Greater than 3,000 (39%), 1,000 – 2,999 (15%), 500 – 999 (5%), 201 – 499 (12%), Below 200 (29%). Gross annual revenue of the organizations represented among participants indicated nearly all were between $1 billion - $10 billion (89%), with the rest greater than $10 billion. Overall, it was determined that there was representation from a variety of industries:

- Industrials 22%
- Information Technology 20%
- Professional Services 20%
- Financials 15%
- Health Care 12%

<10% (in order): Not for profit, Materials, Real Estate.

# 4. RESULTS

## 4.1. Problems with SWOT

Since Hill and Westbrook (1997) observed a lack of analytic rigor in how practitioners were generating factors for SWOT, practitioners were asked to rate on a Likert scale (5=always, 1=never) how often they generated factors by consulting data and conducting analyses. Findings revealed that all results were statistically significant to 0.1% and greater than neutral (3.0) which indicates that they often generate factors by consulting both secondary and primary data and by conducting analyses (Table 3). These findings contradict Hill and Westbrook's observation as practitioners do appear to be generating factors by conducting analyses and consulting primary and secondary data sources.

**Table 3.** Descriptive statistics for the methods used to generate factors for SWOT (N=41) and (df=40).

| | *M* | *SD* | *t* | *Sig.* |
|---|---|---|---|---|
| Consulting secondary data | 3.73 | 1.245 | 3.762 | ** |
| Conducting analyses | 3.61 | 1.115 | 3.501 | ** |
| Consulting primary data | 3.54 | 1.098 | 3.130 | ** |

Note(s): M = mean; SD = standard deviation; n.s. = not significant; * = p <0.05; ** = p <0.01; ***= p <0.001

Hill and Westbrook (1997) proposed that practitioners had no means of limiting the number of factors generated for SWOT. Practitioners were asked to what extent they typically have too many factors per category on a 5-point Likert scale (5=always, 1=never) and t-test results indicated that practitioners' ratings were greater than neutral (3.0), suggesting that practitioners may at times have too many factors per category. Practitioners were also asked to identify the typical number of factors generated per category in the model. Results indicated five to six (43%) was most common followed by three to four factors (40%), seven to eight (15%) and nine to ten (3%) factors. Despite most practitioners only having three to six factors per category, Likert results indicate practitioners rated that there were too many factors per category. As such, these findings are consistent with Hill and Westbrook and infer that there still appears to be no means of limiting the number of factors generated.

According to Hill and Westbrook (1997), practitioners had no means of prioritizing factors. Results of the survey revealed that based on the 5-point Likert scale of agreement (5=strongly agree, 1=strongly disagree), responses were statistically significant to 0.1% and were greater than neutral (3.0). These results indicate that practitioners agree that they have some understanding of which factors are more important than others (Table 4). Since practitioners appear to have a means of prioritizing factors, the results contrast the findings by Hill and Westbrook.

**Table 4.** Descriptive statistics for the extent to which practitioners agree with the following (N=41) and (df=40).

| | *M* | *SD* | *t* | *Sig.* |
|---|---|---|---|---|
| I typically have a clear understanding of which factors are more important than others | 3.49 | .898 | 3.479 | ** |

Note(s): M = mean; SD = standard deviation; n.s. = not significant; * = p <0.05; ** = p <0.01; ***= p <0.001

Considering Valentin (2001) had proposed in the RBV that certain types of resources could be more valuable to competitive advantage than others, practitioners were asked exploratory questions regarding which tangible and intangible resources were most important to SWOT on a 5-point Likert scale (5=very important, 1=not at all important). The results indicated that Informational ($\mu$=4.24), Relational ($\mu$=4.10), Reputational ($\mu$=3.73), Human ($\mu$=3.63), and Organizational ($\mu$=3.63) resources were significantly greater than neutral (3.0) at 0.1% significance level, and Financial ($\mu$=3.46) and Intellectual ($\mu$=3.34) were significantly greater than neutral (3.0) at the .05% significance level (Table 5). The remaining categories of Legal and Physical resources failed to reach statistical significance, inferring both are considered to be of neutral importance. These exploratory findings suggest that a resource's ability to facilitate competitive advantage for the organization may be one approach current practitioners are using to prioritize factors.

**Table 5**. Descriptive statistics for the extent to which practitioners identify the following types of resources as important to a typical SWOT (N=41) and (df=40).

| | M | SD | t | Sig. |
|---|---|---|---|---|
| Informational | 4.24 | .799 | 9.964 | *** |
| Relational | 4.10 | .735 | 9.561 | *** |
| Reputational | 3.73 | 1.096 | 4.275 | *** |
| Human | 3.63 | 1.090 | 3.726 | *** |
| Organizational | 3.63 | .942 | 4.309 | *** |
| Financial | 3.46 | 1.247 | 2.380 | * |
| Intellectual | 3.34 | 1.063 | 2.056 | * |
| Legal | 3.02 | 1.235 | 0.123 | n.s. |
| Physical | 2.78 | 1.255 | -1.120 | n.s. |

Note(s): M = mean; SD = standard deviation; n.s. = not significant; * = p <0.05; ** = p <0.01; ***= p <0.001

The problems of defining factors with ambiguous words or unclear words were also examined in this survey (Hill & Westbrook, 1997). Practitioners were asked on a 5-point Likert scale how frequently (5=always, 1=never) a factor is defined with ambiguous words and with unclear words, respectively. The results were insignificant or neutral (3.0) on the frequency at which they define factors with ambiguous words and unclear words, respectively. These results suggest that practitioners may at times be defining factors with ambiguous or unclear words, which aligns with the observations by Hill and Westbrook.

Another problem identified by Hill and Westbrook (1997) was that practitioners have no means of resolving conflicts when factors belong to multiple categories. Practitioners were asked how frequently a factor belongs to multiple categories in a typical SWOT on a 5-point Likert scale (5=always, 1=never) to determine whether such conflicts were being resolved. The results were insignificant or neutral (3.0) for the frequency at which a factor belongs to multiple categories, suggesting that practitioners may at times have factors that belong to multiple categories. Since practitioners are still experiencing this problem, the results are consistent with the observations of Hill and Westbrook (1997) and infer that practitioners may not have a means of resolving conflicts when a factor does belong to multiple categories.

This study also examined the problem of whether practitioners had no logical link to implementation and whether practitioners only conducted a single level of analysis, as observed by Hill and Westbrook (1997). In order to test the link to implementation, practitioners were asked to rate on a 5-point Likert scale (5=always, 1=never) how frequently insights from SWOT were implemented directly into strategy development. Practitioners' responses were significantly greater than neutral at the 0.1% significance level, indicating that insights were frequently implemented directly into strategy development. In order to test whether practitioners conducted a single level of analysis, practitioners were asked to rate on a 5-point Likert scale how frequently (5=always, 1=never) insights from SWOT are combined with another analytic technique. The results were significantly greater than neutral at the 0.1% level, suggesting that practitioners are conducting more than one level of analysis. These findings contradict the observations of Hill and Westbrook (1997) because practitioners appear to be linking SWOT to strategy development and practitioners are combining SWOT with additional analytic techniques (Table 6).

**Table 6.** Descriptive statistics for the frequency at which practitioners self-report the following happens while conducting SWOT (N=41) and (df=40).

| | *M* | *SD* | *t* | *Sig.* |
|---|---|---|---|---|
| Insights from SWOT are implemented directly into strategy development. | 3.78 | .936 | 5.341 | *** |
| Insights from a SWOT are typically combined with another analytic technique. | 3.93 | 1.058 | 5.609 | *** |

Note(s): M = mean; SD = standard deviation; n.s. = not significant; * = p <0.05; ** = p <0.01; ***= p <0.001

A follow-up exploratory question sought to reveal which of the analytic techniques identified by Ghazinoory, et al., (2011) practitioners used in combination with SWOT. The results showed that most practitioners combined SWOT insights with the following analytic techniques:

- Environmental 37%
- Balanced Scorecard Analysis 20%
- Statistical Analysis 20%
- Multiple Criteria Decision Matrix 15%
- Cross-impact Analysis 7%

<10% (in order): Cross-impact Analysis, Analytic Hierarchy Process, Porter's Five Forces, Porter's 4 Corners, Win/Loss Analysis, Salesforce/CRM Data, Scenario Analysis, and Keep, Stop, Start Analysis.

### 4.2. Proposed conditions for SWOT

In addition to the proposed problems of SWOT, the survey examined whether practitioners are conducting SWOT in the best the conditions proposed in the literature. The first condition by Ghazinoory et al., (2011) was that SWOT should be conducted as a structured business process. When practitioners were asked on a 5-point Likert scale how frequently (5=always, 1=never) they conducted SWOT as a structured, step-by-step process, the responses were neutral (3.0) and failed to reach statistical significance. Based on the survey results, this infers that practitioners do not appear to be consistently conducting SWOT as a structured business process, contradicting Ghazinoory, et al.

The second condition proposed by Ghazinoory et al., (2011) was that SWOT should be conducted in a stable market environment. According to the U.S. Bureau of Labor Statistics, the median monthly unemployment rate was 5.5%, which was determined to be low considering national average over the last 10 years is 5.7%. The median monthly personal consumption expenditures was $12,432 billion and the median quarterly gross private domestic investment was $3,206 billion, both of which were considered to be high based on national average over the last 10 years (U.S. Bureau of Economic Analysis). The median annual inflation of consumer prices in the U.S. was 1.8%, which was considered to be low compared to an average of 2.0% over the last decade (World Bank). Since the median value for unemployment and inflation were low and personal consumption expenditures and gross private domestic investment were high, these findings suggest that practitioners have been conducting SWOT in a stable market environment over the last decade as proposed by Ghazinoory, et al., (Table 7).

**Table 7.** Descriptive statistics for economic indicators between January 2011 and January 2021.

| | M | SD |
|---|---|---|
| Unemployment Rate | 5.5% | 2.1% |
| Personal Consumption Expenditures | $12,432B | $1,306B |
| Gross Private Domestic Investment | $3,206B | $478B |
| Inflation, Consumer Prices in the U.S. | 1.8% | 1.2% |

A complete summary of the hypotheses testing results is presented in Table 8.

**Table 8.** Hypothesis testing results.

| | | |
|---|---|---|
| H1. | Practitioners are experiencing the problems identified by Hill and Westbrook (1997) while conducting SWOT. | Partially supported |
| $H1_a$ | Practitioners do not verify factors with primary data. | Not supported |
| $H1_b$ | Practitioners do not verify factors with secondary data. | Not supported |
| $H1_c$ | Practitioners do not verify factors with analyses. | Not supported |
| $H1_d$ | Practitioners have no means of limiting the number of factors generated. | Supported |
| $H1_e$ | Practitioners have no means of prioritizing factors. | Not supported |
| $H1_f$ | Practitioners are defining factors with unclear terms. | Supported |
| $H1_g$ | Practitioners are defining factors with ambiguous terms. | Supported |
| $H1_h$ | Practitioners have no means of resolving conflicts. | Supported |

| | | |
|---|---|---|
| $H1_i$ | Practitioners are experiencing a problem because there is no logical link to implementation. | Not supported |
| $H1_j$ | Practitioners are experiencing a problem because only a single level of analysis is required. | Not supported |
| H2. | Practitioners are conducting SWOT in the best conditions as proposed by Ghazinoory, et. al., (2011). | Partially supported |
| $H2_a$ | Practitioners are conducting SWOT as a structured business process. | Not supported |
| $H2_b$ | Practitioners are conducting SWOT in a stable market environment. | Supported |

## 5. DISCUSSION

The present study drew upon the works of Hill and Westbrook (1997) and Ghazinoory, et al., (2011) to identify whether practitioners experienced problems with SWOT and conducted SWOT in the best conditions proposed in the literature, respectively.

The findings show that while practitioners resolved some of the problems with SWOT identified by Hill and Westbrook (1997), four issues persist today. The first problem is that practitioners indicated that they may have too many factors per category. The next two problems are that practitioners appear to be defining factors with ambiguous words and unclear words, respectively. Finally, the last problem is that practitioners may not have a means for resolving conflicts when factors could belong to multiple categories (e.g., opportunity and threat). This feedback more clearly identifies issues with SWOT from the practitioner perspective and provides valuable insight into improving the methodology.

Although the findings indicate that these issues with SWOT persist, exploratory findings offer a glimpse into how practitioners may be leveraging their industry expertise in an attempt to overcome these issues. For example, the practitioners indicated that Informational and Relational resources were particularly important for SWOT whereas Legal and Physical resources were not. These findings suggest that practitioners recognize the relative importance of different types of resources and may be limiting the number of strengths and weaknesses included in the SWOT to only the most important resources, especially considering that Industrials, Information Technology, and Professional Services were the leading industries represented in the study.

In addition to these four problems, the findings also show that practitioners are not conducting SWOT in the optimal conditions as proposed by Ghazinoory et al., (2011). Specifically, the findings indicated that practitioners may not be consistently conducting SWOT as a structured business process. This feedback is particularly insightful and actionable for practitioners because establishing a more structured business process for SWOT is an optimal condition that is actually within the control of an organization's capabilities.

In contrast, while practitioners were conducting SWOT in a stable market environment over the last decade, the relative stability of the market environment is outside of the control of an organization. As such, the optimal conditions as proposed by Ghazinoory et al., (2011) reveals a void in that a more robust SWOT model may be needed for unstable market environments. Although beyond the scope of this study, exploratory findings suggest that practitioners may already be experimenting with new ways to build a more robust SWOT model. For example, the analytic technique used most frequently in combination with SWOT among practitioners today was Environmental Analysis which is focused exclusively on better understanding disruptions in the macro-environment and often falls under the responsibility of a CI function. Practitioners may be using Environmental Analysis to overcome this void with SWOT and as such, additional analytic techniques may offer a starting point in strengthening SWOT for more volatile macro-environments.

This study represents one of the first empirical studies to capture feedback directly from practitioners on how SWOT is conducted in the workforce today. The findings identified the problem areas that still persist and the suboptimal condition that may be undermining the value of a SWOT. Collectively, these findings provide a roadmap for future research to develop a stronger and more robust SWOT methodology that better serves current practitioners.

## 6. CONCLUSION

The present study was a pilot test and represents one of the first attempts to empirically evaluate the SWOT process among current day practitioners. The results of the study help to close the academic-practitioner divide by identifying four ongoing issues with SWOT and revealing the suboptimal condition from the literature that still persist among practitioners.

A few limitations in the present study included potentially ambiguous questions related to SWOT, the relatively small sample size, and the limited sampling frame during survey collection. In order to mitigate these concerns, a pre-test for the survey instrument was conducted to identify and correct any issues with question ambiguity before beginning survey collection. Furthermore, filter questions and invitations to strategy and intelligence-specific LinkedIn groups were used to ensure a representative sample of the target population. Although the sampling frame is limited, the respondents in the sample reflect the target population of practitioners who have conducted SWOT in the workforce and as such provide invaluable insights.

Future research efforts could focus on establishing a clearer understanding of why some problems persist with such a long-standing strategic management tool and whether new solutions could help practitioners overcome these problems. For example, such research could explore the role business and intelligence programs play in training practitioners on SWOT and how that may impact the manifestation and persistence of these problems. Research could also explore whether conducting SWOT in collaboration with new technologies or additional strategic management tools could offer solutions for practitioners to overcome these issues.

Another opportunity for future research is to more clearly define the optimal conditions for conducting SWOT. This could prove highly relevant as practitioners conduct SWOT while navigating unique market dynamics or disruptive technologies (e.g., artificial intelligence) at any given time. For example, such research could explore whether practitioners agree that conducting SWOT as a structured, step-by-step business process is the best practice during more turbulent markets. Furthermore, research could explore opportunities for practitioners to incorporate other strategic management tools at various steps within the SWOT process to strengthen and build a more robust strategic management tool that can adapt to both stable and unstable macro-environments. The application and adaptation with other analytic techniques identified in this study may offer a starting point.

The practitioner feedback captured by this research provides a roadmap for future research to continue elevating the managerial relevance in the SWOT literature and closing the academic-practitioner divide on one of the most popular strategic management tools today.

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The authors of this paper hereby affirm that the submission has not been previously published and has not been submitted to or is not under review by another journal or under consideration for publication elsewhere, and, if accepted, it will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright- holder.

The authors also affirm that there is no conflict of interest.

The anonymized research data will be made available if required and if the university ethics board permits.

To the best of our knowledge there is no copyright material in this paper.

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Stevan Didijer
1911-2004

# The Role of Business Intelligence Tools in the Decision Making Process and Performance

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**ABSTRACT** In the current turbulent business markets, the way companies address and tackle unexpected events is reflective of its success. Different varieties of technological tools have been created to assist in overcoming unpredictable and unexpected events in businesses that cold impact them, and one such tool is the business intelligent. Such systems assist in gathering data concerning business operations and environments transforming information into something that can be easily understood. Major firms have adopted big data analytic systems but this does not hold true for most universities and organizations literature has yet to present the way business intelligence tools affect businesses of different types. Therefore, in this study, the impact of business intelligence tools on the decision-making and performance of public universities in Jordan is investigated.
This qualitative study was conducted on 200 members in 10 chosen universities. Based on the interview results, BI tools deployed in the universities assist in facilitating timely decision-making, enhances efficiency of performance and meets client's needs suitably, leading to employee satisfaction.

**KEYWORDS**: business intelligence tools, competitive advantage, customer satisfaction, employee satisfaction and universities.
**JEL Classification**: M15

## 1. INTRODUCTION

There are two fundamental meanings to business intelligence (BI) based on its relationship with the term, 'intelligence'. The first less often used meaning is the capacity of human intelligence used in business activities or affairs. In other words, business intelligence as a new field of investigation of the application of the human cognitive faculties and AI technologies to decision-making and management support for resolving business issues. The second meaning is related to intelligence as valuable information where value is in terms of currency and relevance – it refers to expert information, knowledge and technologies used in managing businesses. Under this meaning, business intelligence is a general category of applications and technologies used for collecting, accessing, and analyzing data to assist in decision-makers to make informed decisions. Moreover, business intelligence is a term that indicates the ownership of comprehensive knowledge of the entire factors affecting business and thus, firms need to known about these factors (e.g., customers, rivals, business partners, economic surrounding and internal operations) for effective and informed quality business decisions. Moreover, a distinct business intelligence field referred to as competitive intelligence is focused only on the external competitive surroundings of the firm. The firm collects information regarding the competitors' actions and makes decisions on its basis. No serious attempt has been made to gather internal information.
However, in current business organizations, because of automation, technological development and increasing standards, vast amounts of data are being generated, and data warehouse technologies have been developed for data storage. Such warehouse

technologies include Improved Extract, Transform, Load (ETL) and Enterprise Application Integration tools enabling timely data collection. Similarly, OLAP reporting technologies enabled the faster reports generation which carries out data analysis. On the whole, business intelligence has become an art of going through vast data amounts, extracting what is important, and transforming it into knowledge that is useful for decision-making. Therefore, in this paper, the author examines the BI concept, its components, emergence, benefits, and the factors that influence it, technology requirements, BI design and implementation, cultural imperatives and different BI techniques. The paper would contribute to the understanding of the basic concepts of BI.

## 2. BUSINESS INTELLIGENCE

Business intelligence is the process of obtaining vast data mounts, analyzing them and presenting them in the form of quality reports that contain a summarized version of the data essence based on business actions, allowing management to make daily business decisions (Abusweilem & Abualoush, 2019). According to (Alyan, 2022), BI is a method of enhancing the performance of business through the provision of robust assistance to decision-making, enabling access to actionable information. Essentially, BI tools are technology that facilitates efficient business operations through the provision of increased value to information for effective use. BI, based on Alzghoul et al. (2022) refers to the process of gathering, treating and diffusing information to reduce uncertainty in decision-making. Other researchers described it as a business management term that describes applications and technologies functioning together to collect, access and analyze data concerning the business for informed decisions.

Moreover, Arefin et al. (2022) described one of the fundamental characteristics of BI tool as its ability to gather data from a source that is heterogeneous and through the use of advanced analytical methods, the demands of users can be met. BI technology was classified by Bach et al. (2018) based on the information delivery method, namely reporting, statistical analysis, ad-hoc analysis and predictive analysis and the Gartner Group brought up the BI concept and defined it as, a set of methodologies and technologies (J2EE, DOTNET, Web Services, XML, data warehouse, OLAP, Data Mining, representation technologies, among others, to enhance the effectiveness of enterprise operations, and support decision-making for competitive advantages.

In the current times, BI is no longer a new technology but rather it is considered as an integrated solution for firms that focus on their requirement as a key factor driving technology innovation. Thus, the way key business issues are identified and addressed is the major challenge of BI applications to achieve valuable impact on business. BI was stated to include effective data warehouse and reactive element that oversees the time critical operations, enabling tactical and operational decision-makers to modify their actions based on the strategy of the company Božič, K., & Dimovski, 2019). Another definition came from Chen & Lin (2021), who described BI as the result of in-depth analysis of detailed business data, with the inclusion of database and application technologies and practices of analysis. The authors further extended the definition of to include technical tools that cover knowledge management, decision support systems, enterprise resource planning and data mining. Other authors included several software for Extraction, Transformation and Loading (ETL) data warehousing, database query and reporting under BI (Gauzelin & Bentz, 2017) as well as multidimensional/online analytical processing (OLAP) data analysis, data mining and visualization.

## 3. BUSINESS INTELLIGENCE TOOLS

The following are tools of BI: OLAP (on-line analytical processing) – this is the way business users can go through data through the use of sophisticated tools that enable dimensional navigation (e.g., time and hierarchies). OLAP provides multidimensional, summarized business data and is utilized for the purpose of reporting, analysis, business modeling or planning optimization. OLAP has methods and tools that are useful in working with data warehouses or data marts created for state-of-the-art enterprise intelligence systems. The systems are essentially used to process questions directed towards trends determination and critical factors analysis. Reporting software produces the aggregated data views to maintain an informed management concerning their business status.

BI tools used for storing and analyzing data like data mining and data warehouses, decision support systems and forecasting, document warehouses and document management, mapping, information visualization, and knowledge management. This also includes dash boarding, geographic information systems, management information systems, trend analysis, software as a service (SaaS), advanced analytics, and forecasting/predictive analytics, which leverages statistical analysis methods for the prediction of accurate facts measurements.

Corporate Performance Management (Portals, Scorecards Dashboards) – under this category, a container exists for the pieces to plug into in order to create an aggregate story; for instance, a balanced scorecard displays portlets for financial metrics coupled with universal learning and growth metrics. In this regard, real time BI enables the real time distribution of metrics using email, messaging systems and interactive displays.

Data Warehouse and Data Marts – this is an important BI component, which is subject and oriented and integrated. It supports the physical data propagation through the several enterprise records integration, cleansing, aggregation and query tasks. Often times it contains the operational data, which is referred to as updateable set of integrated data used for the wide tactical decision-making in the enterprise. It constitutes live data and not snapshots with minimal history retained.

Data Sources - data may be sourced from historical data, operational data, external data, market research firms, online data or information from an existing data warehouse. Also, the data sources may take the form of relational databases or data structure supporting the existing business applications, and they may also exist in various platforms and can possess structured information (e.g., tables, spreadsheets) or unstructured ones (e.g., plaintext files, pictures and multimedia information).

Moving on to data mart, it is referred to as a collection of subject areas that are organized to support decisions that are made by specific departments, with every department, having their separate data mart. Marketing data mart is similar to other data marts but it should be noted that individual departments do have their own hardware, software, data and programs that comprise the data mart and each interpret their data mart's structure that meets specific needs.

Moreover, data marts are like data warehouses in that they store operational data that is useful for strategizing based on past trends and experiences analysis. The major difference is that the data mart is developed based on distinct, pre-defined needs for a specific grouping and configuration of chosen data – which is why there can be several data marts within a business enterprise. It can support a specific function, process or unit in the business organization and it is a collection of subject areas organized to support decisions of a specific department concerning its needs.

BI tools have been extensively accepted as the new middleware between transactional applications and decision support applications, thereby decoupling systems focused on facilitating business transactions efficiency from those focused-on business decisions support efficiency. BI is capable of decision support, online analytical processing, statistical analysis, forecasting and data mining.

## 4. ISSUES IN BI: EXPERTS DIFFERENT VIEWS OF BI

Experts in data warehousing consider BI as a supplementary system that is still a novelty. They view it as a technology platform that supports decision-making and it appears that data mining experts also view it as a set of advanced decision support system coupled with data mining methods and algorithms applications. In the viewpoint of statisticians, BI is a forecasting analysis-based tool that has several dimensions. It has been mentioned time and time again that the key to BI system success is the consolidation of data from various different enterprise operational systems into an enterprise data warehouse but in the case of universities, a full-fledged enterprise data warehouse is still a rarity because of the effort scope required towards the consolidation of the whole enterprise data.

According to Daradkeh et al. (2022), because of the newly emerging highly dynamic business environment, only enterprises that are competitive will be successful in sustaining their market status. With regards to universities, they can only stand out if they leverage information on their market place, customers and operations to grab business opportunities. In this regard, the right information needs to be analyzed and several commonly used surveys like Gartner, Forrester and International Data Center indicated that majority of the firms all over the world are inclined towards investing in BI, with the top major investments poured into Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) in the past decade because due to the information gathered by the systems most of them achieve competitive advantage. The main objective of any corporate entity is to aim for the right access to information at the right time and thus firms need to facilitate information analysis and application to make timely decisions for their operations and processes. This may be exemplified by the marking of seasonal merchandise or provision of specific customer recommendations, where the firms have to access information as fast as they can and through the implementation of smarter business processes like business intelligence tools, such processes may influence the firm's bottom line and value of returns.

## 5. FUTURE OF BUSINESS INTELLIGENCE

In the rapidly evolving business world, consumers demand efficient and timely services and to remain competitive, it is crucial for firms to meet or exceed the consumers' demands or expectations. Firms need to largely depend on BI systems to be able to lead trends and future events. BI users have been demanding real time BI or the next best thing, specifically to use in their frontline operations, expecting to obtain up to date information in a way that is similar to monitoring stock quotes online. In other words, weekly/monthly analysis is no longer sufficient and in the near future, businesses will become dependent on real time business information in the same way that they obtain information by just clicking on the internet. The near future also sees businesses to expect democratized information whereby university users will be enabled to see information on their specific segment in light of performance. The future demands BI tools to increase to match the increase in the expectations of consumers. Therefore, it is crucial for businesses to increase the pace of services to remain relevant.

## 6. REASONS FOR ADOPTING BUSINESS INTELLIGENCE

In the context of universities, BI facilitates accurate and informed decisions and hence, it can function as a tool of competitive advantage – this is particularly true for firms that extrapolate information from indicators in their surroundings, based on which they can accurately predict future trends and economic conditions. After gathering BI effectively and proactively used, decisions can be made for their benefit, with the ultimate aim being to improve the timeliness and quality of information generated. This is akin to having a lead on a race with the clear road ahead. BI reveals the firm's position compared to its rivals, customer behavior changes and patterns of spending, firm capabilities, market conditions, future trends, demographic and economic information, and social, regulatory and political environment.

## 7. RESEARCH METHOD

This qualitative descriptive study used semi-structured interviews with members of the universities for data collection regarding BIT issues (Grublješič et al., 2019) and the emerging themes deciphered from the interviews were highlighted. Two hundred

(200) research participants were recruited from public Jordanian universities staff the semi-structured interview (refer to Appendix I and II) comprised of questions concerning BIT aspects and the participants were queried on each of them after which the answers were coded and analyzed and the emerging themes listed (refer to Table 1).

**Table 1**. A summary of universities academic staff responses on several parts of BI tools

| Business Intelligence tools Aspects Tested Through Interviews | Yes% | No% |
|---|---|---|
| Placement of Business Intelligence tools | 50 | 65 |
| Usage of Business Intelligence tools at all universities levels | 20 | 80 |
| Difficulty of the Business Intelligence tools deployed | 40 | 60 |
| Obtainability of expert staffs for accomplish Business Intelligence tools | 30 | 80 |
| Business Intelligence tools support in decision making | 90 | 10 |
| Different influences of Business Intelligence tools different than helping in decision making | 99 | 10 |
| Awareness on maintenance of the practice of Business Intelligence tools | 95 | 5 |

## 8. RESEARCH RESULTS

On the basis of the obtained results, the summarized responses of the respondents concerning several BI system aspects and the perceptions of universities academic staff are displayed in Table 1 and Table 2.

| Business intelligence tools aspects tested through junior employee interviews | Yes% | No% |
|---|---|---|
| Practice of at the universities | 20 | 90 |
| Familiarity with BIT | 30 | 90 |
| BIT influence on employee production and presentation | 75 | 35 |
| BIT impact on firm performance | 70 | 30 |
| Opinions on continuation of BIT use | 90 | 20 |

## 9. ANALYSIS

The themes that emerged from the interview responses were regarding BIT deployment and use among universities from the perception of junior employees and managers.

### 9.1. BIT Deployment and Usage

Majority of the universities have not deployed BIT and among the 50 top management employees who were part of the interviews, only 45% acknowledged their universities implementation of BIT. The junior employees were generally unsure as to their universities have implemented BIT or not, and only 15% were of the consensus of BIT use. From the managers, 19% indicated the use of BI throughout the levels of universities, indicating the deployment and use of BIT has not yet proliferated throughout all the employees. The results are consistent with (Vallurupalli, & Bose,2018) result which showed that small businesses have not completely embraced BIT. The authors proceeded to explain that the costly BIT are the reasons for their economic unfeasibility for universities and this makes them unattractive to such institutions. Universities are often on a tight budget and are thus convinced that BIT investments would be a waste of resources.
The second barrier to universities adoption of BIT is the lack of IT systems in the institutions as noted Wahua & Ahlijah (2020). It appears that small business entities lack sufficient computer equipment for hosting BIT (Yiu & Cheng, 2021; Tripathi etal., 2020). Generally speaking, computer equipment's are capital intensive and universities just do not have enough budget to invest them being cost-saving institutions and thus, this limits their opportunities to adopt BIT. According to Yeboah-Boateng and Tripathi et al., (2020) universities lack the right installation capabilities and they are

not inclined towards business functions online as this may compromise security. In cloud-based services, business intelligence functions are sometimes hosted online and thus, owing to the universities lack of trust in online processes, they prefer not to adopt BIT.

**9.2. BIT Complexity and Availability of BI Maintenance Personnel**

Another theme that arose from the interviews is the lack of available skilled BI maintenance personnel and BIT complexity. Based on the results, majority of the managers (61%) are of the consensus that BIT implementation would be full of complexity and 39% stated that they only have basic BIT in their firms. Moreover, regardless of the confirmation of the majority of respondents that universities have deployed complex BIT, the results indicated that personnel needed to maintain the systems are lacking. The results showed that only 25% of the managers agreed to the capable handling of their skilled employees of BIT, and the managers' responses are aligned with those of the employees in that 20% of the latter possess BIT knowledge. Therefore, universities who had enough skilled employees been the ones who embraced complex BIT.

In a related study, Huang et al., (2022) described complexity as the level to which an innovation is viewed as difficult to understand or use. In this regard, complexity remains one of the barriers to innovation/technology adoption as less complex technologies are more likely to be adopted compared to complex technologies, which is why in the former, high adoption rate was noted (Jaklič et al., 2018). BIT complexity stems from the mathematical functions that are useful for predicting a specific phenomenon to resolve an issue. Skills in IT are crucial for BIT use (Jaradat et al, 2022). The interviews revealed that majority of the employees do not have sufficient knowledge on BIT and this could have been affected by their lack of IT skills.

Added to the IT skills are the mathematical skills which are needed for BIT adoption and use. Universities lack the resources and personnel for BIT management – they have limited resources that may prevent them from adopting BIT (Jayakrishnan et al., 2018). Furthermore, universities have high rate of failure in attracting qualified personnel for BIT management as they do not have the resources to pay them.

**9.3. Impact of BIT on Universities performance**

The third theme noted in the interviews is the impact of BIT on the institutions of higher learning as based on the results, 89% of the interviewed managers contended that BIT facilitate decision-making in their institutions. For instance, one of the managers admitted, "Our company, though categorized as a university has deployed BIT, which provide real-time data". Information from BIT is essential for a lot of processes, like the registration of low number of sales which was later attributed by the system to the expensive price of the product. This information is real-time stemming from market intelligence, enabling the companies to resolve the product price, and ultimately enhance sales". This admission shows that BIT is capable of providing technological tools that facilitate decision-making based on accurate data. Essentially, owing to the high uncertainty in market trends and the competitiveness, valuable information is difficult to come by and in this regard, BIT enable business efficiency as they generate timely information for decision-making. Aside from generating such information, BIT also provides data quality in that information is free from error and highly analyzed, ready for the leaders to interpret the results. BIT is thus significant as it enables firms to identify changing trends and emerging threats to resolve them before they can do any damage. According to one of the respondents, "In our company, we rely on business intelligence solely for market scanning.

The interview results are consistent with Khan., (2022), who contended that a firm needs constant provision of information regarding consumer behavior and changing preferences and this is provided by BIT in a timely manner so that informed decisions can be made (Masa'Deh et al., 2021). Apparently, BIT is crucial for assisting leaders of companies to take timely decisions and front-line employees and executives to make informed decisions. BIT include historical data and combine it with real-time data as needed by the business leaders, empowering them to make quick decisions with confidence as the provided information is valid and reliable. The system generates information based on the past while at the same time considering the present situation, and incorporating expected changes (Torres et al., 2018). They extract factual data from a vast amount of unstructured data and transform it into meaningful and actionable reports, which is important for making informed decisions in the universities. Businesses largely depend on BIT to source reliable data for their decisions and aside from reliable information, BIT also has several other benefits.

The interview results showed that almost all of the interviewed managers (95%) were of the consensus that BIT provides several benefits aside from timely decision making. For instance, one of them contributed that, "BI is not just amount timely decision-making as it helps businesses in many other ways, like providing vital information used to mitigate errors in production, enabling the company to achieve efficiency in operations". Notably, one of the benefits of BIT that were mentioned by the managers is the increased efficiency and productivity of the universities. This is consistent with Melo & Machado (2019), who stated that informed strategic decisions obtained from BIT are important in enhancing efficiency in operations and productivity in business. In this line of argument, BIT is capable of analyzing emails and chats between customers and the company to determine customer characteristics and demands, paving the way form higher strategic plans to address such needs through enhanced operations for competitive advantage and goal achievement.

From the interview results, the interviewees perceived that BIT provides information that is important and accurate directed towards enhancing the company's efficiency and productivity. BIT was also mentioned to affect return on investments (ROI) and similar to this, Wieder Nithya & Kiruthika, R. (2021) revealed that BI paves the way for businesses to mitigate costs, increase revenues and profit margins and it impacts ROI by offering a cost-effective method of collecting business information. Businesses used to channel vast amounts of cash to conduct market research to obtain information how to increase their efficiency but currently, BI provides cost and time-saving strategy of gathering the same if not more information. Hence, financial resources that were used to carry out market research can be directed towards other functions that need it. The ROI is also affected by BIT as they enhance the productivity of employees (Nuseir et al., 2021).

As for the interviewed employees, majority of them (70%) were in agreement that BI fosters their work performance and productivity, and in turn, enhance the overall company performance. One junior employee stated, "Our company has made use of BIT as a norm in all operations. At the onset, after the system's implementation, we thought that it was a way for the leaders to control use but eventually we were convinced that the system noted each employee's productivity, which is a vital owing to the need to support and empower those who are low-performing. The report may also be used by managers and supervisors to find the right strategy to motivate low-performing employees to enhance their performance and thus, I find BIT to be crucial to both performance and productivity". It is notable that BIT assists in the productivity and performance enhancement of employees and they assist leaders in how to encourage and motivate such performance (Rahardja & Harahap, 2019). Motivating employees is a must if the company is to meet their satisfaction and obtain their loyalty.

## 10. PERCEPTIONS OF UNIVERSITY MEMBERS ON THE USE OF BIT

It is evident from the results that managers and junior employees alike in the universities hold positive views on BIT use, with 96% of managers convinced of the need for continued usage. This held true for 85% of the employees who were also convinced of its usefulness and the need for ongoing use.

Such responses may be related to the BIT provided benefits. Regardless of the company size, BIT provides enhanced and timely strategic decision-making, meets customer satisfaction and motivates the work force (Rahman, 2021). These benefits are coupled with enhanced performance of the universities.

## 11. CONCLUSION

The study findings evidenced the extensive effects of BIT on the university's operations. BIT brings about decision-making of management through the provision of data that is timely, quality and accurate, considering the past, present and future events, thereby enabling leaders to reached informed decisions. Added to this, BIT deployment in universities goes beyond decision-making resolution but also enhancing employees' performance, customer satisfaction and firm functions and processes. They promote and maintain efficient operations to meet customer needs and present reports on the individual performance of employees in order to support and motivate them. On the whole, BIT impact enhances the performance of companies, which is a result that is consistent with that found in universities in Sweden, and thus, it can be argued that there appears to be universal behavior among universities. Finally, BIT enhancement of universities performance can be used as a BIT outcome indicator – one of the top challenges that businesses generally face. BIT is important for monitoring universities performance Richards et al., 2019), with performance generally determined through the comparison between goals and outcomes. BIT performance among universities calls for focusing on several dimensions (i.e., financial, operational and overall effectiveness), which need to be determined through subjective and objective means (Saleem & Ilkhanizadeh, 2021; Siripipatthanakul & Phayaphrom, 2021). There is thus a need to conduct a holistic determination of the overall impact and outcome in universities ranging from financial performance, to employee satisfaction, and customer satisfaction.

## Author Contribution

Business intelligence (BI) is the decision-making serving structure,Therefore, BI aids kind improved choices, and it has developed prevalent in numerous administrations, it is significant to illustration BI's rule concluded DMPs and to display how the paraphernalia used in BI enable the DMP. "Higher teaching organizations global are working nowadays in a actual active and multifaceted situation" As a outcome, universities that are within advanced teaching are vulnerable for rivalry is thoughtful. Additionally, developed teaching is additional part that will theoretically influence large statistics study Therefore, the request and usage of big data in advanced instructive organizations might consequence in improved excellence teaching for scholars and a better involvement for the university members. This study the first study in my country explain the role of BI tools in the decisions making process at the public universities.

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1911-2004

# The Role of Competitive Intelligence in Improving Performance through Organizational Learning, A case study Start-ups in Algeria

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**ABSTRACT** The study aims at identifying the role of competitive intelligence in improving company performance through organizational learning in start-ups, Relied on a descriptive-analytical approach with the use of a questionnaire to collect data, which was distributed to a random sample of 255 Start-ups in Algeria. The structural equation modelling was also used through the Smart pls 4 program to test the study's hypotheses.
The study concluded that there is a weak indirect role between competitive intelligence and the performance through organizational learning expressed in a correlation coefficient estimated at 23.1%, while the direct role was greater with a correlation coefficient of 61.6%.This is due to the fact that the mediator variable does not play its active role in strengthening the relationship between competitive intelligence and the start-ups performance despite this impact, start-ups in Algeria does not effectively carry out research to obtain available opportunities in the market.

**KEYWORDS**: competitor intelligence, market intelligence, organizational learning, start-ups, the performance

## 1. INTRODUCTION:

Business companies today face a range of difficulties regardless of their size or nature of work, as the resulting risks from unexpected changes in the environment are due to its successive changes, which in turn have an impact on the performance which requires experiment and practice methods and approaches that enable them to survive and compete in the market, including competitive intelligence. Among these methods is competitive intelligence, which in turn is a process that includes gathering analysing and communicating information about the environment to help in strategic decision-making (Dish man & Calf, 2008, p. 767).As it refers to the behaviour used by both companies and nations to enhance competitiveness through better use of information for a company to effectively benefit from competitive intelligence efforts and operations (Moloi & Iyamu, 2015, p. 3), there must be a proper organizational awareness and a competitive culture(Saayman & al, 2008, p. 383). Despite the fact that competitive intelligence serves as a highly important tool for the company's strategy, represented in the planning, management, and official exploration of the marketing strategy model for the company (Safarnia, 2011, p. 2) . Its purpose was to analyse information about competitors' activities, trends in a specific sector, and the market in general, in order to guide the

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company in achieving its goals and objectives (Artur, 2020, p. 2).

In order to ensure sustainability and continuity, companies work on improving their performance to reach high levels and have a competitive advantage. This trend has led to the emergence of human resources as a strategic supplier and a key element for creativity, learning, and technology creation. This is reflected through competitive intelligence and its role in improving organizational performance, as it has the ability to effectively produce goods and services that meet market demand (quality, term, and growth) and contributes to the economic system's movement (Lorino, 1991, p. 56) . Performance is a positive attribute that companies can achieve for a certain period of time, resulting in positive outcomes compared to others. Performance in companies is subject to the measurement and evaluation process which helps the company ensure that all departments perform their various tasks with the highest possible efficiency. It also determines the outcomes that need to be achieved and the evaluation that is carried out independently by the relevant authority (Fermon & Grandjean, 2015, p. 1). Performance management should be properly administered as it is a system that sets goals and connects individual goals with organizational ones by defining the objectives and expectations towards each individual, followed by providing incentives that align with their performance (Lorraine Dori Ponu & Zubair, 2015, p. 2).

This study aims at achieving objectives related to clarifying the different concepts that pertain to competitive intelligence and organizational learning, the performance of the company, and to identify if the start-ups in Algeria have orientations and procedures aimed at developing the role of competitive intelligence in improving the institution's performance through organizational learning.

The study derives its importance from the role that competitive intelligence plays in improving the performance of start-ups in Algeria through organizational learning. The significance of the study also lies in the fact that it deals with a recent topic in the field of scientific research in Algeria and the scarcity of studies and research related to it, as it is one of the first studies that applies competitive intelligence in start-ups in Algeria. Therefore, we look forward that it will be a reference for specialized scientific studies and a practical guide for start-ups.

The descriptive and analytical approach was adopted, by defining the variables of the study both theoretically represented by the variables of competitive intelligence and organizational learning, and performance of the company. In terms of the practical aspect, data was collected through a questionnaire designed and distributed to a sample of start-ups in Algeria. To process and test the study's hypotheses, structural equation modelling was used through the smart pls 4 program.

## 2. LITERATURES REVIEW:

In this element, we will delve into the concepts related to competitive intelligence, organizational learning, and performance.

### 2.1. Competitive intelligence:

Competitive intelligence is providing companies with the tools to make informed decisions. It is enabling companies to keep ahead of the competition and industry trends (Maune, Mobile Applications Adoption and Use in Strategic Competitive Intelligence: A Structural Equation Modelling Approach, 2022, p. 65), Competitive intelligence is defined are considered a crucial tool for the company's strategy represented in the formal planning, management and exploration process of its marketing strategy model (Safarnia, 2011, p. 2), where the latter includes the optimal use of public sources for developing data related to the competitive and market environment (Maune, 2014, p. 61) . Competitive intelligence is also considered as behaviour used by companies and countries alike as a means to improve competitiveness through the best use of information (Moloi & Iyamu, 2015, p. 3). Besides, the importance of competitive intelligence lies in shaping strategic marketing decisions and building for companies aimed towards the market, given its fundamental role in central marketing decisions and the company, with the latter focusing on monitoring the competitive environment to provide actionable intelligence to enhance the company's competitiveness (Macinnis & al, 2002, p. 179) .

Competitor's intelligence aims to assess the risks and opportunities in a competitive environment before they become apparent, this process is called early signal analysis, being a highly specialized activity where it has become necessary to design tools and means that can assist analysts in competitor intelligence in the process of collecting analyzing benefiting from knowledge and coming up with strategies effective work (Lipika & al, 2011, p. 2). Additionally, competitive intelligence also aims to analyze information about competitor activities and trends in a specific sector and the market in general, in order to guide the institution in achieving its goals and objectives (Artur, 2020, p. 2) .

Market intelligence is the set of means that enable managers to be constantly aware of developments in the market environment (Kotler & autres, 2006, p. 84). It is a strategy that links a company's activities, resources and capabilities to its external environment with the goal of maximizing current and future performance and converting current goals into more meaningful and achievable ones from both functional and operational perspectives (Johnson & Scholes, 1993, p. 20) . The latter affects the planning process both in the long and short run, and adds value to the company's strategic decision-making as well (Lackman & al, 2000, p. 6). Additionally, market intelligence studies the relationship between intelligence acquired through the internet, value creation, and variables such as customer relationships, innovation, productivity, and the efficiency of these connections (Rahchamani & all, 2019, p. 58).

Market intelligence performs a set of core functions that support strategic marketing information. It aims to fulfil the marketing goals of a company by determining the information needs of the intended strategic marketing objectives and conducting research to gather and deliver that information, processed appropriately for management, as well as executive managers who require intelligent data to develop and implement related marketing strategies. Furthermore, market intelligence has the role of identifying business operations and techniques represented in the on-going information search, which contributes to improving the quality of strategic marketing programs. Finally, the role of predicting the future is for intelligence to be more effective when it can act proactively, in other words, anticipating future events (Лена, 2019, p. 3).

**2.2. Organizational learning:**

Organizational learning is considered as a collective phenomenon for acquiring and forming competencies that can be more or less profound or sustainable. It leads to a change in the way situations are managed or in the situations themselves (bounfo, 1998, p. 182) .Organizational learning is also a means through which individuals in companies continuously discover how they shape the reality they work in and how they can change it (peter & al, 1994, p. 59) . Companies are considered large repository of knowledge, as their success depends on converting implicit knowledge into an explicit one, which is shared among the company's members (Marshall & al, 2004, p. 16). Organizational learning is a multi-level process in which individuals acquire knowledge through work and thinking together, and it is also a process of improving practices through better understanding, developing vision, knowledge, and connecting past and future practices and activities (Hillary, 2018, p. 3).

Organizational learning is composed of a set of elements that may come about through partnerships and alliances, as it generates a large accumulation of knowledge. Through this, the value and importance of the company increases, paralleling its assets, innovations, employee loyalty and customer satisfaction (stephen, 2000, p. 8). Additionally, learning companies are distinctive in that they are leadership-oriented, either transformational or transactional. As transactional leadership is encountered in such a way which helps leaders understand the appropriate way to achieve desired goals. As for transformational leadership, it is a new type in which it motivates employees to work together for the long term (jeery & Ann, 1999, p. 19). The more the scope of learning companies expands, the stronger the culture it creates, which leads to increased learning and is reflected in the results and development of the companies (Raanan & al, 2007, p. 66).

**2.3. The Performance:**

The subject of performance is considered to be of great importance in managing companies, considering its ability to ensure the sustainability and achievement of balance between the satisfaction of stakeholders and employees (Drucker, 1999, p. 73). The performance represents the values and principles prevailing in the organizations internal work environment, which regulate work strategies, ideas and visions that help develop the organization and ensure its continuity (Mbaindin, 2022), It is also considered as the ability to produce goods and services effectively in response to market demand (quality, deadline, growth), allowing for a surplus to move the economic system (Lorino, 1991, p. 56). Performance consists of three main elements, represented by efficiency, effectiveness, and potency. Efficiency refers to the relationship between the resources allocated and the results achieved, while effectiveness refers to the level of goal attainment. As for potency, it is the degree to which a companies able to reach its goals and achieve them. Therefore, performance is considered as a concept that reflects both the goals and the necessary means to achieve them (Brosquet, 1989, p. 1).

Furthermore, all companies should measure the effectiveness of their activities and the results of their work, because the information obtained will lead them towards achieving their goals and thus improving their performance. Therefore, a company that cannot measure its performance cannot monitor it, if it is so, it cannot manage it, and as a result, it will not be able to make sound decisions Performance measurement is important because it helps the company to ensure that all departments are performing their various tasks with the highest possible efficiency (Lingle & Schiermann, 1996, p. 56). It also provides a benchmark for evaluating the performance outcomes, as well as an independent evaluation by the relevant authority. It measures the level of achievement (Fermon & Grandjean, 2015, p. 1) .

Performance management is a system that involves setting performance goals, defining measures, evaluating performance and providing feedback. This allows for the identification of training needs and the development of performance, as well as determining the reward system (Solkova Andrea & Gabriela, 2013, p. 20). As it links individual goals with organizational ones by clarifying expectations for each individual and then offering rewards that are aligned with their performance (Lorraine Dori Ponu & Zubair, 2015, p. 2).

The performance process in the company is subjected to the evaluation process, as the latter plays an important role by looking at the reasons and also concerned with the goals and ways to achieve them. It is a broader process as it considers the causes, also concerned with the goals and ways to achieve them (Lauras, 2004, p. 112).

**2.4. Research questions:**

Through this study, we will address the role of competitive intelligence in improving the performance of start-ups in Algeria through organizational learning. However, this study differs from previous ones in that it takes into account a mediator variable represented by organizational learning, unlike other studies, it dealt with each variable separately, and it also focuses on start-ups in Algeria. On this basis, the following problematic was raised:

**- What is the role of competitive intelligence in improving the performance of start-ups in Algeria through organizational learning?**

As a preliminary answer to the problematic, the following main hypothesis was adopted:

There is a strong positive correlation with statistical significance at a 0.05 level of competitive intelligence in improving the performance of start-ups in Algeria through organizational learning.

**3. DATA AND METHOD:**

In order to test the hypotheses of the study and to reach results about the role of competitive intelligence in improving the performance of the company through organizational learning, start-ups in Algeria were studied as a case study.

### 3.1. Study Population and Sample:

The study population was made up of all 756 start-ups in Algeria. A simple random sample was selected using the equation of Steven Thompson, with a size of 255 start-ups. 231 start-ups that were suitable for analysis were retrieved, resulting in a response rate of90.58% (Thompson, 2012, p. 51).

### 3.2. Analysis and Presentation of the Study Tool:

In order to test the relationships between the variables of the study and to build a standard model while ensuring its validity, a questionnaire was designed which included (20) questions divided into three axes. The first one is concerned with competitive intelligence with questions ranging from 01 to 08. The second deals with organizational learning from 09 to 12, while the third is about organizational performance from 12 to 20.

The variable representation statements of the study model that combines the latent and measured variables should be represented in order to test the biases .e. the extent to which the questions are able to express and measure the real variable, it was found that there are statements that do not achieve the required minimum of 70%, and this can be clarified through the following table:

**Table 1.** Examine the question ramifications of the modified default form

| Latent variables | | paragraphes | Saturation coefficient |
|---|---|---|---|
| Competitive intelligence | Competitor intelligence | M1 | **0,857** |
| | | M2 | **0,861** |
| | | M3 | **0,598** |
| | | M4 | **0,762** |
| | Market intelligence | MA1 | **0,872** |
| | | MA2 | **0,812** |
| | | MA3 | **0,705** |
| | | MA4 | **0,849** |
| Organizational Learning | | O1 | **0,579** |
| | | O2 | **0,558** |
| | | O3 | **0,841** |
| | | O4 | **0,879** |
| Company performance | Efficiency | K1 | **0,795** |
| | | K2 | **0,744** |
| | | K3 | **0,794** |
| | | K4 | **0,751** |
| | Effectiveness | F1 | **0,117** |
| | | F2 | **0,881** |
| | | F3 | **0,937** |
| | | F4 | **0,686** |

**Source:** Prepared by researchers using smart pls 4

From Table 1, it can be seen that there are indicators less than 70% in the dependent variable "Performance of the company F1", and this variable has been previously removed.

However, despite the fact that there are indicators that do not comply with the condition, they are not less than 40%, but they were kept in the model because they increase the composite reliability values or the average variance, as the following figure shows the adjusted study model after the mentioned indicators are removed.

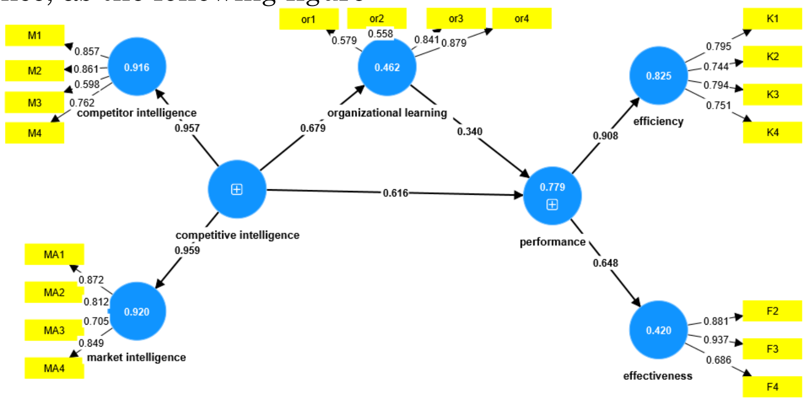


**Figure 1**. The modified model

**3.3. Reliability evaluation:**

By measuring the reliability of the study tool, the Alpha Cronbach index was relied on and reinforced with the composite reliability index CR, and the results were as shown in the table below:

**Table 2.** The value of the alpha Cronbach and the RHO indicator

| Variants | | Alpha Cronbach | Indicator RHO | Vehicle Reliability |
|---|---|---|---|---|
| Competitive intelligence | Competitor intelligence | 0,774 | 0,798 | 0,857 |
| | Market intelligence | 0,826 | 0,838 | 0,895 |
| Organizational Learning | | 0,725 | 0,869 | 0,814 |
| Company performance | Efficiency | 0,774 | 0,777 | 0,854 |
| | Effectiveness | 0,792 | 0,845 | 0,878 |

**Source:** Prepared by researchers using smart pls 4

As seen from the previous Table 2, all of the alpha Cronbach's coefficients are greater than 0.7, and the RHO values are also high and exceed 0.70. This makes it possible to rely on the proposed questionnaire, and the CR index is greater than 0.7 in all dimensions. Therefore, it can be said that the study tool is characterized by reliability.

**3.4. Measure of Convergent Validity:**

It is determined that the model has convergent validity if the accepted AVE value is greater than or equal to 0.50, meaning that the model explains more than half of the variance in its indicators. The following table shows average variance extracted AVE:

**Table 3.** The asymptotic validity measure of the model

| Variants | | Extracted average variance |
|---|---|---|
| Competitive intelligence | Competitor intelligence | 0,604 |
| | Market intelligence | 0,659 |

| Organizational Learning | | 0,532 |
|---|---|---|
| Company performance | Efficiency | 0,595 |
| | Effectiveness | 0,709 |

**Source:** Prepared by researchers using smart pls 4

From the Table 3, we note that all AVE values are accepted from a statistical standpoint because they are greater than 0.50. Thus, it can be determined that the model has convergent validity.

**3.5. The $R^2$ determination coefficient test:**

In this stage, the values of the determination coefficient that relates to the overall impact of the factors, (the independent variables dependent on the dependent variables through the mediator ones), are calculated. The following table shows the results of the determination coefficient:

**Table 4.** The coefficient of determination $R^2$

| Variants | $R^2$ | $R^2$Adjusted |
|---|---|---|
| Company performance | 0,776 | 0,774 |
| Organizational Learning | 0,460 | 0,457 |
| Effectiveness | 0,437 | 0,434 |
| Efficiency | 0,814 | 0,813 |
| Market intelligence | 0,920 | 0,919 |
| Competitor intelligence | 0,916 | 0,915 |

**Source:** Prepared by researchers using smart pls 4

According to the Table 4, it is noted that all coefficients are positive and statistically acceptable, where competitive intelligence explains 0.46 of the organizational learning, which is a mediator interpretation. However, competitive intelligence and organizational learning together explain 0.72 of the company performance, which is a large interpretation. It is similar to the modified coefficient of determination, where its results are close to the results of the coefficient of determination, to indicate the predictive quality of the model.

**3.6. Evaluating Model Validity:**

After confirming the validity of the measurement model, we move on to evaluating the validity of the previously determined building model. This is by calculating the conformity quality index using the GOF. The calculation is done using the following formula:

$$\text{GOF}= \sqrt{\overline{AVE} \times \overline{R^2}}$$

$$GOF = \sqrt{0.619 \times 0.720}$$

$$GOF = 0.667$$

Therefore, with a GOF of 0.66, which is greater than 0.36, the model is characterized by high quality.

**3.7. Results analysis:**

The significance of the paths is confirmed by relying on the bootstrapping technique by generating 500 partial samples. The results were as shown in the following figure:

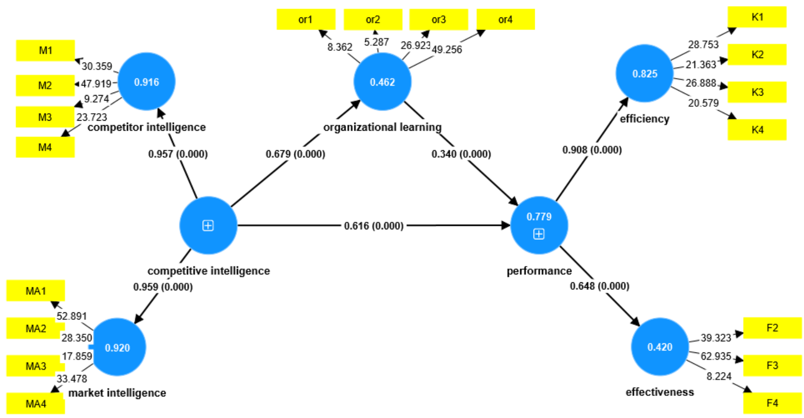


**Figure 2.**Statistical significance of thpaths of the structural model.

### 3.8. Paths analysis:

The following table illustrates the results obtained from the analysis of the relationship paths between the model variables.

**Table 5.** The results of the structural model trajectories analysis

| paths | Paths value | T-value | Std. Dev | P-value |
|---|---|---|---|---|
| Company performance ; Effectiveness | 0,648 | 10,272 | 0,064 | 0,000 |
| Company performance ; Efficiency | 0,908 | 51,520 | 0,018 | 0,000 |
| Organizational Learning ; Company performance | 0,340 | 7,496 | 0,043 | 0,000 |
| Competitive intelligence ; Company performance | 0,616 | 15,006 | 0,041 | 0,000 |
| Competitive intelligence ; Organizational Learning | 0,679 | 19,796 | 0,034 | 0,000 |
| Competitive intelligence ; Market intelligence | 0,959 | 154,049 | 0,006 | 0,000 |

**Source:** Prepared by researchers using smart pls 4

The previous Table 5; indicates that all the model coefficient paths have statistical significance at a level less than 0.05, which indicates the presence of a relationship between the model structural variables, meaning:

- There is a statistically significant positive relationship between competitive intelligence and organizational learning.
- There is a statistically significant positive relationship between organizational learning and the company's performance.
- There is a statistically significant relationship between competitive intelligence and company's performance.

### 3.9. Hypothesis Testing:

The sub-hypotheses and the main hypothesis will be tested in order to determine the impact of competitive intelligence on the performance of start-ups in Algeria through organizational learning.

**-First Hypothesis Test:**

There is a statistically significant relationship at a level of 0.05 between competitive intelligence and organizational learning in start-ups in Algeria.

**Table 6.** The results of the first hypothesis.

| paths | Beta | Std. Dev | Value T | P Value |
|---|---|---|---|---|
| **Competitive intelligence ; Organizational Learning** | 0,679 | 0,034 | 19,796 | **0,000** |

**Source:** Prepared by researchers using smart pls 4

According to the Table 6, the correlation coefficient between the variables is 0.679, which indicates a positive correlation that

aggregates the variables and is characterized by being a mediator relationship. Furthermore, we notice that this correlation is statistically significant at the level of 0.000 which is less than 0.05. Thus, we reject the null hypothesis and accept the alternative hypothesis which states that: there is a statistically significant relationship at a level of 0.05 between competitive intelligence and organizational learning in start-ups in Algeria.

**-Second Hypothesis Test:**
There is a statistically significant relationship at a level of 0.05 between organizational learning and performance of start-ups in Algeria.

**Table 7.**The results of the second hypothesis

| paths | Beta | Std. Dev | T Value | P Value |
|---|---|---|---|---|
| **Organizational Learning ; Company performance** | 0,340 | 0,043 | 7,946 | 0,000 |

**Source:** Prepared by researchers using smart pls 4

From the table 7, we note that the correlation coefficient between the variables is 0.340, indicating a positive weak relationship that is characterized by a weak relationship between the variables. Additionally, this correlation is statistically significant at a significance level of 0.000 which is less than 0.05. Thus, we reject the null hypothesis and accept the alternative hypothesis which states that there is a statistically significant relationship at a level of 0.05 between organizational learning and performance of start-ups in Algeria.

**-Third hypothesis test:**
There is a statistically significant relationship at the 0.05 level of significance between competitive intelligence and the performance of start-ups in Algeria.

**Table 8.** The results of the third hypothesis

| paths | Beta | Std. Dev | T Value | P Value |
|---|---|---|---|---|
| **Competitive intelligence ; Company performance** | 0,616 | 0,041 | 15,006 | 0,000 |

**Source:** Prepared by researchers using smart pls 4

From the table 8, we note that the correlation coefficient between the variables is 0.616, indicating a positive and strong relationship between the variables. This correlation is statistically significant at a level of 0.000 which is less than 0.05. Therefore, we reject the null hypothesis and accept the alternative hypothesis which states: There is a statistically significant relationship at the 0.05 level of significance between competitive intelligence and the performance of start-ups in Algeria.

**-The main hypothesis test:**

There is a strong positive correlation with statistical significance at a level of 0.05 between competitive intelligence and performance of start-up in Algeria through organizational learning.

**Table 9.** The results of the main hypothesis test.

| paths | Std. Dev | Beta | P value | T value |
|---|---|---|---|---|
| **Competitive intelligence; Organizational Learning; Company performance.** | 0.032 | 0,231 | 0,000 | 7,218 |

**Source:** Prepared by researchers using smart pls 4

From the table 9, we notice that the correlation coefficient between the variables is 0.231, indicating a positive correlation that combines the variables together, and which is characterized by a weak relationship. We also note that this correlation is statistically significant at a level of 0.000, which is less than 0.05. Therefore, we reject the null hypothesis and accept the alternative hypothesis which states that: There is a statistically significant role at a level of 0.05 for competitive intelligence in improving the performance of start-up in Algeria through organizational learning.

## 4. RESULTS:

The study reached a set of results related to competitive intelligence and its role in improving the performance of start-ups in Algeria through organizational learning. It was concluded that competitive intelligence is part of the strategic information management process, which is necessary for the company's strategies, as it assists to understand the methods and strategies used by competitors to gain and sustain a competitive advantage, and that organizational learning is the main driving force for improving organizational performance. It was also concluded that there is a relationship between competitive intelligence and the company's performance with an average degree estimated at 61.6%, Despite this impact, start-ups in Algeria do not effectively carry out research to obtain available opportunities in the market. This direct relationship between competitive intelligence and the performance of start-ups was better than the indirect relationship through organizational learning as a mediator variable, which was weak, estimated at 23.1%. This is due to the fact that the mediator variable does not play its active role in strengthening the relationship between competitive intelligence and the start-ups performance. Through a review of the results and the correlational relationships, it was concluded that the reason for the weakness of the impact is due to the fact that start-ups in Algeria do not work on updating their programs for developing their employees' skills and providing training and education programs on the one hand, and on the other hand, they do not do a good job in analyzing their competitors and early detection of risks and opportunities available to them.

## 5. CONCLUSION:

Competitive intelligence is considered one of the most significant systematic operations that work to improve the performance of a company through organizational learning. It is a solid foundation in the field of making strategic decisions and determining the priorities of the company intelligence requirements to lead the path of competitive intelligence in terms of collecting, analyzing and distributing information. It aims to determine the purpose and new sources of competitive advantage identify strengths and weaknesses of competitors and their reactions, as well as to identify the priorities of agreement on research and development activities.

Based on previous results, we recommend that start-ups in Algeria prioritize competitive intelligence as a necessary means of making strategic decisions in the company, which helps improve its performance. They should also give more consideration to organizational learning, as it is the process through which the company aims to improve its overall capabilities, develop itself, activate its relationships with its environment, adapt to its internal and external variables, and mobilize its employees to be more attentive in following and acquiring knowledge for the purpose of development and excellence. Besides, it is also essential to conduct on-going and continuous improvement processes for competitive intelligence, which assists achieve a competitive advantage. Additionally, start-ups in Algeria should also pay more attention to organizational learning in order to achieve its expected role in improving the relationship between competitive intelligence and organizational performance and to provide training and education programs for individuals. Furthermore, they should conduct research to identify available opportunities and use modern systems and methods for analyzing their competitors.

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Stevan Didijer
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# Artificial Intelligence and Morality: A Social Responsibility

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**ABSTRACT** Both the globe and technology are growing more quickly than ever. Artificial intelligence's design and algorithm are being called into question as its deployment becomes more widespread, raising moral and ethical issues. We use artificial intelligence in a variety of industries to improve skill, service, and performance. Hence, it has both proponents and opponents. AI uses a given collection of data to derive action or knowledge. There is therefore always a chance that it will contain some inaccurate information. Since artificial intelligence is created by scientists and engineers, it will always present issues with accountability, responsibility, and system reliability. There is great potential for economic development, societal advancement, and improved human security and safety thanks to artificial intelligence.

**KEYWORDS**: Artificial Intelligence, Morality, Ethics, Intelligence, Accountability, Social Responsibility

## 1. INTRODUCTION

We already have Artificial Intelligence (AI), and many of its applications are currently in the early stages of development. Whether, if ever, other, far more sophisticated kinds of AI, such as superintelligence, will exist, is a matter of debate. Many people believe that the development of superintelligence is inevitable; there are the typical

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disagreements on when it will arrive as well as whether we should welcome it and why. In the discussions over whether we will ever construct AI that has awareness and that is sufficiently complex and in the correct ways to merit our moral concerns and protection, philosophical and technical disputes overlap.

One of the burning subjects of the twenty-first century is the ethical issues raised by artificial intelligence (AI). The use of robots in dangerous situations is one of the many alleged possible advantages of AI, which also includes operational enhancements such as a decrease in human error (for example, in medical diagnosis) (e.g., to secure a nuclear plant after an accident). AI also brings up a number of ethical issues, including grave safety and health problems, algorithmic unfairness, and the digital divide. Artificial intelligence (AI) ethics is a discipline that has emerged in response to the growing concern over the potential consequences of AI.

Artificial intelligence can be used in a wide range of fields and in several contexts within a single field. In the field of medicine, artificial intelligence (AI) may play a role in computerised patient diagnosis or in algorithms that analyse massive amounts of data from hundreds or millions of patients to better understand the nature of disease and health. It might provide automated or online responses during patient consultations and even therapeutic sessions. AI may be used in robotic surgery help for difficult and sensitive procedures. It might be connected to mobile technology that informs individuals about their own illnesses or remote health monitoring. It might provide nursing and care along with robotic companions or aides. Robots are being used to help autistic persons learn social skills. Robotic dogs are being created to offer dementia patients companionship and mental stimulation. Robotic limbs are being created, along with tools that will help people with locked-in syndrome and other illnesses interact.

### 1.2 Ethics or Morality

The concept of ethics is difficult, nuanced, and confusing. The moral principles dictating a person's, or a group of people's conduct can be referred to as ethics (Nalini, 2019). In other words, ethics are a system of principles, standards, or laws that help individuals make moral decisions. Ethics, in general, is the study of good and evil as well as the moral roles and responsibilities of people and groups.

There have been more high-profile instances of harm brought on by either technology misuse (such as voter manipulation using psychometrics, surveillance using facial recognition, bulk data gathering without authorization, etc.) or technology design defects (e.g., bias in cases of recidivism, loan denial, and medical misdiagnosis, etc.). What characteristics ethical AI have? Or anything in general that is ethical? Practically speaking, being ethical entails abiding by and upholding moral principles and doing what is "the right thing to do," as well as not harming others. Instead of addressing the issue of whether something is lawful, ethics address the issue of what is right and wrong. An artificial intelligence (AI) is said to be ethical when it is developed on moral principles and with the goal of enhancing society rather than just maximising financial gain. Responsible AI refers to the development of AI that preserves the principles of equity, openness and explainability, human-centeredness, and privacy and security.

In our opinion, the study of AI ethics is still in its infancy and is a subset of the larger area of digital ethics, which examines the moral questions raised by the development and use of cutting-edge technologies like blockchain, big data analytics, and AI.

## 2. LITERATURE REVIEW

Because AI's versatility and wide range of uses are one of its most noticeable features. It has been noted that a technological capability is hailed as AI until it is implemented, at which point, in the words of John McCarthy, the computer scientist who coined the phrase "artificial intelligence," claiming that "as soon as it works, no one calls it AI anymore" and that its definition is problematic. It might be difficult to distinguish what constitutes true AI from other types of technology. Some AI systems are so deeply ingrained in modern technology that we hardly even notice them.

This also means that, in many instances, it is difficult or impossible to determine which ethical and other value dilemmas are brought by AI and other technology.
Ethics has a long history, which is a reflection of its enduring importance to human life, whereas AI has only recently experienced significant growth. Yet during the past decade or two, the power and promise of AI have grown incredibly quickly.

brings to light the critical necessity of addressing the numerous ethical challenges it raises. We might be living in a world in a few years when a large number of the decisions that affect our lives—from the financial markets to transportation, from health care to military operations—are either made by AI systems or heavily influenced by them.

**2.1 Concept of Artificial Intelligence**

In the presence of experts from many fields, John McCarthy (1970) discussed and introduced the phrase "Artificial intelligence" at the summer workshop organised by the Dartmouth summer research project in the year 1956. Artificial intelligence is the study and application of science and engineering to the development of intelligent devices, particularly intelligent computer programmes (AI). McCarthy reportedly chose artificial intelligence because of its objectivity, that the machine can be constructed and used to replicate the attribute of intelligence which is specified clearly. The term AI is such a broad field, it cannot be defined by a single definition. According to Blackman (2022), Artificial Intelligence is defined as "a computerized system that demonstrates behaviour that is usually assumed to require intelligence."

**2.1.1.Background of AI**

It is unknown who started working on artificial intelligence technology first, however, it is said that Alan Turing was the first as there is a record that states that he has deliver lectures on artificial technology in 1947 he was a mathematician by profession during world war II self-motivated people started voluntarily working on the artificial intelligence machines as mentioned by Muller (2020) and additionally, turning is said to be the first to express his opinion as programming is more powerful than building machines. By the late 1950s, numerous researchers were relying on AI, and the majority of them were built on computer programming. Christopher Strachey made a significant step forward in 1951 when he created the first artificial intelligence software. Although mathematician Alan Turing had previously published the most well-known work, "Computer and Machinery Intelligence," a year prior, the naming ceremony for "Artificial intelligence" was slated for 1956. He posed the query, "Can Machines Think?," to everyone. He also put the techniques to the test as he put up the idea that computers may be trained to learn much like a young child. He wanted to know the solution to this problem. By developing the first artificial intelligence programme in 1951, Christopher Strachey accomplished a tremendous advancement. He created computer programmes for checkers games that are played on Manchester's Ferranti University's Mark I computer. Also, until 1952, they made a few little adjustments before speeding up the programme. They were finally able to show off the better game in the summer.
The initial artificial intelligence software to operate in the US was a checkers program developed for the IBM 701 prototype in 1952. Arthur Samuel took over the essential elements of Strachey's checker's program and considerably expanded it over the course of several years. In 1955, he developed features that enabled the software to absorb experience. Samuel made his program better by incorporating tools for rote memorization and generalization. As a result, in 1962, the programme won one game against a previous Connecticut checkers champion. A lower number of volunteers and more issues made the next years difficult for AI, but things began to improve at the beginning of the 1990s. The worldwide situation was becoming more discouraging, and artificial intelligence challenges were outpacing solutions.

**2.2. Why do ethical issues with AI keep popping up?**

One of the most incredible and frequently made allegations is that AI poses a "existential threat" to humans. Some claim that an AI may evolve vigorously and spontaneously, much like a cancer that is exponentially smart. We may start out with something simple, but intelligence evolves in ways that are out of our control, according to Muller (2020). The struggle for survival will soon involve the entire human race Why do so many people hold diametrically opposed opinions about the possible advantages and dangers of AI? Hollywood is to blame, as is so often the case. We can take the example of films like The Matrix into consideration. The AI in these drawings, however, is portrayed as intelligent, supremely powerful, and in control of either a military arsenal or invulnerable robots. Yet, AI as we currently understand it is just a collection of complex computer algorithms. Given the state of technology, the vast majority of clichés about AI consuming the world are therefore untrue. Following are the main reasons that are causes for raise in the ethical issues.

***i. Manipulative AI:***

*The private sector had the chance to monetize user data properly, but* instead decided against it. As a result, it is now the responsibility of the federal government to ensure that manipulative AI practices are stopped. The government learned from the creation of antitrust laws when it realized the risks associated with select businesses dominating and controlling markets. As a result, legislation was passed to promote free competition and safeguard consumers from predatory business activities. When it comes to AI-driven online data collection, the same needs to happen. Information that will help them profile people was provided by Facebook Cambridge Analytica (2022). Numerous businesses will profit financially by using artificial intelligence to investigate user biases. The user may develop an addiction as a result of adopting artificial intelligence strategies. one might come across this use case in the gaming and gambling sector. Another example is the current Facebook Analytica controversy from the 2016 US election, which used voter behavior as a lever to change the outcome.

***ii. Privacy:***

AI technology must priorities respecting people's rights to privacy and information, and consumers must be given unequivocal assurances regarding the handling and security of their personally identifiable information. protecting their privacy. Data about an individual should always be the main factor considered while gathering, analysing, exchanging, and interpreting data. By defining data access, ownership, and permission, it is done. Research on privacy have typically concentrated on governmental organizations, but over time, the term privacy has been widened to cover any individual, group, or detective. I. C. Education (2021) states that although technology has advanced and had a big impact over time, government rules have not changed much. Because of this, new technologies like artificial intelligence are still open to abuse by powerful groups or individuals. The rate of digitization is accelerating faster than expected. Today, every document and piece of personally identifiable information is digitized. Every information gathered, whether knowingly or unknowingly, is accessible online. Also, many sensors produce a variety of data on people. The potential for clever data collecting and analysis is increased by the application of artificial intelligence. A security-related agency or agent will then begin to monitor you as a result. As a result, agents share information in exchange for payments. Pesapane, Tantrige, et al. (2020) stated that the information they gathered in exchange for a free service was user information, which is extremely valuable when compared to their prices. For instance, facial recognition technology can be used to recognize a person from a collection of images or videos, allowing for the building of a digital profile of that individual.

***iii. Lack of Transparency:***

The "black box" designs, which hide the reasoning behind each AI decision, are a branch of the decisions made by artificial intelligence. It brings up the issue of machine-human trust. The fairness metric disappears, excluding people from the decision-making process. It raises the issue of systemic prejudices. Moreover, data is used by artificial intelligence systems. The truth of it is unknown. It merely predicts patterns based on previously discovered patterns. Muller (2020) guarantees that adding quality data into decision-making processes will increase their quality, but there is still a long way to go until artificial intelligence is sufficiently sophisticated to distinguish between good and bad input. Winikoff and Sardelik (2021), for example, claimed that when Apple debuted its new credit card, artificial intelligence was used to tack on interest to the user. Women were charged a higher interest rate than men, which was seen as discriminatory.

### 2.3. Necessity of Morality or Ethics in AI?

In the above section, we have seen the causes for the rising of the ethical issues in the field of AI. In this section, one must understand the need of morality or ethics to be followed practicing AI.
To include ethics into artificial intelligence, following issues must be resolved.

**2.3.1. Privacy:** The users' psychological, emotional, intellectual, physical, and digital safety should be protected by maintaining information security, say the AI Now Institute (2022) and Blackman (2022). In order to reduce security risks and boost user confidence in system outcomes, platforms incorporating AI-powered technologies need to be constantly guarded against potential attacks.

**2.3.2. Accountability:** Transparency is required for technical decisions to be held responsible. Every choice should be explained to the parties concerned so they can understand why it was made. According to the AI Now Institute (2022) and Blackman (2022), Accountability enhances the likelihood that organizations or people will guarantee the successful implementation of artificial intelligence systems they design, develop, operate, or deploy over the course of their lifetime, in complete compliance with their obligations and applicable laws and guidelines, and will demonstrate this through their actions and suggestions.

**2.3.3. Freedom:** The global level of living shouldn't be threatened by technology. It could harm freedom since individual can be tracked and profiled based on certain beliefs and actions.

**2.3.4.** Since it is difficult to know how a model arrives at a certain result, the term "black box models" is widely used to characterize machine learning methodologies, particularly deep learning models. Human-readable explanation of the machine's reasoning This level of transparency is required to build learners' trust in artificial intelligence systems and ensure that they can understand why a model comes to a particular result.

## 3. AI ETHICS

What should ethical AI look like is one of many questions. The simplest definition of ethical AI is that it shouldn't harm people. Yet, what harm? How are human rights implemented? Before creating moral AI, these questions must be resolved. Training in ethical sensitivity is required for moral decision-making. Theoretically, AI should be able to recognize moral ambiguities. How can we make ethically conscious decisions if AI is capable of doing so? Unfortunately, it's difficult to understand and put into practice. It necessitates consistent, continual work. Nonetheless, recognizing the significance of creating ethical AI and beginning to work on it gradually are huge advancements. Companies like Accenture, Microsoft, Google, IBM and Atomium-EISMD are just a few that have begun developing ethical guidelines for the advancement of AI. The FEAT principles for the application of AI were published in November 2018 by the Monetary Authority of Singapore (MAS), Amazon Web Services, and Microsoft. Fairness, ethics, accountability, and transparency are represented by these tenets. The framework for creating ethical AI is shown in Fig. 1. This framework makes it possible to create and use ethical AI. To establish ethical standards for the conception, advancement, and use of AI, it is critical for academics, practitioners, and policymakers to work together. To ensure ethical behavior, protective boundaries are needed with the frameworks and concepts. Regulatory organizations must close a legal loophole in order to ensure the use and observance of such ethical principles. Whether they are based on case law or carried out through responsibilities described by Siau and Wang (2020), these legal and regulatory tools will be crucial for the good governance of AI, which helps to implement and enforce ethics of AI to enable the establishment of ethical AI.

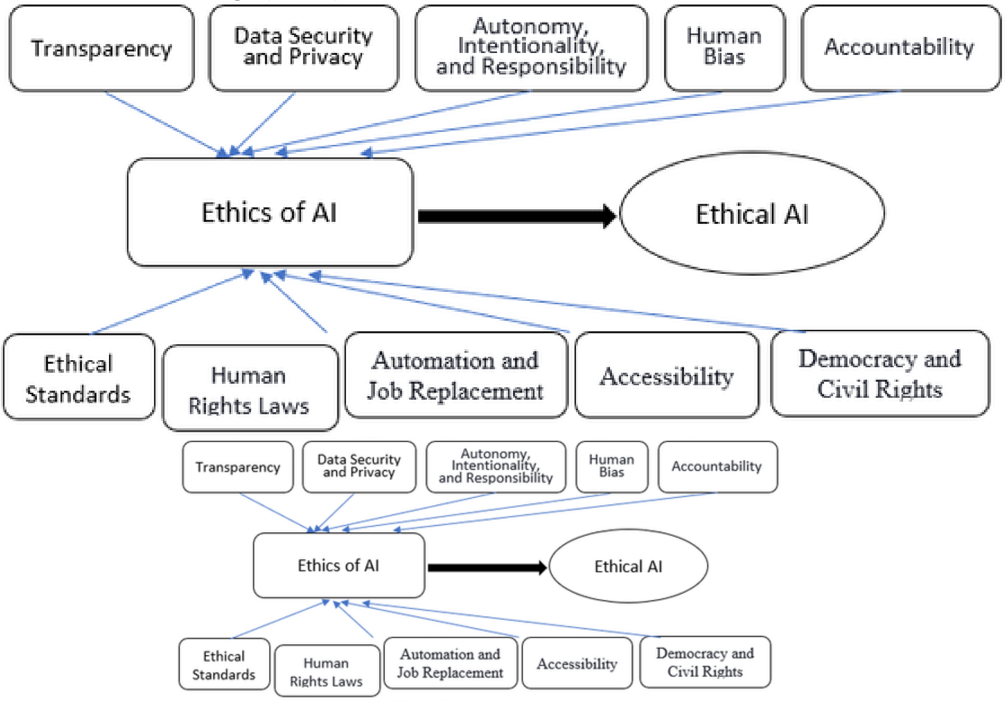


**Figure 1**. AI Ethics: Framework of building ethical AI (Wang and Siau, 2020)

## 4. ORGANIZATION WORKING ON AI MORALITY

Despite the fact that privacy and data engineers and data scientists are not primarily concerned with ethical standards, certain associations have emerged to advance ethical behavior in the artificial intelligence field. Some well-known ethical organizations focusing on AI ethics are listed below.

### 4.1. AlgorithmWatch:

According to Hagendorff (2020) and Tags, AlgorithmWatch is a non-profit research and advocacy group devoted to monitoring, examining, and evaluating the effects of automated decision-making (ADM) systems on people (2022). AlgorithmWatch's goal is to make sure that algorithmic systems are used to benefit all people, not just a small number of individuals. They start promoting algorithmic systems that defend democratic institutions and the rule of law, favoring autonomy over surveillance, civil rights over racial discrimination, independence over power in place of dictatorship, dynamism, justice, and equality in place of prejudice and partiality,

and a sustainable way of life in place of an unethical way of life.

### 4.2. AI Now Institutes:

The mission of the AI Now Institute (2022) is to conduct multidisciplinary research, engage the general public, and ensure that artificial intelligence systems may be applied in a range of social contexts. As per them, we must collaborate with those who will suffer the most from the use of AI to create standards and procedures. This will lessen harm and guide ethical AI deployment. The present research of this institute focuses on privileges and rights, employment and discrimination, and inclusivity and architecture.

### 4.3. DARPA:

The Defense Advanced Research Projects Agency of the US Department of Defense (2022) encourages investigation into and creation of understandable AI. For more than 50 years, DARPA has been a leader in the creation of ground-breaking technologies that have facilitated the deployed rule-based and statistical learning-based AI technologies. According to Hagendorff (2020) and the Center for Human Compatible Artificial Intelligence, the creation and application of "Third Wave" AI systems will allow computers to learn new information using generating circumstances and descriptive models.

### 4.4. CHAI:

"Center for Human-Compatible Artificial Intelligence", a group of universities and institutions working together, is committed to advancing trustworthy AI and technologies that have a clear positive impact. The goal of CHAI is to lay the conceptual and technical groundwork for a shift in AI research's emphasis towards systems that could be perceived as demonstrably helpful. a number of situations and

Ultimately, it appears that computers are becoming far more powerful than living things as a result of ongoing AI research. According to Hagendorff (2020) and Home NSCAI (2021), some of these solutions may have unwanted and possibly long-lasting effects for humans because the solutions produced by such systems are fundamentally unforeseen by humans.

### 4.5. NASCAI:

An oversight committee named “National Security Commission on Artificial Intelligence", considers the means and methodologies to accelerate the advancement of AI, ML, and supporting technologies in order to fully address the needs of the United States' national security and defense. According to Agarwal, Gans, and Goldfarb, Section 1051 of the John S. McCain National Defense Authorization Act established the National Security Commission on AI as a separate committee on August 13, 2018. (2016)

## 5. GOVERNMENT’S OVERNMENT’S INITIATIVE FOR ETHICS IN A

Normally, the government is responsible for ensuring that the ethics are upheld through the regulation of laws and the formulation of policies that take into account societies. The national government as well as the international governments are making great efforts to develop the laws and regulations in light of the developing technology and its use cases. Some non-governmental organizations are working side by side with the government to draught rules to ensure that AI is used ethically. The following are the actions made by various governmental organizations, according to Herbert (2022).

- The US government began developing an AI policy during the presidency of Barack Obama. Their government published two reports on the impacts of AI. The White House designated the NIST to work on the rules for the government's involvement in AI in a note the "American AI Initiative" in 2019.
- Once more in 2020, the Trump administration provided the draught of its "Guidance for Intelligence Applications" policy. The strategy was primarily concerned with investing in the AI industry, with a project aimed at fostering confidence in AI software and addressing privacy concerns.
- New York City passed legislation in December 2021 that forbids New York-based businesses from using AI techniques for personnel screening unless they first check the technology for bias. In January 2023, the law will take effect. Employers must inform candidates if an AI tool is used to decide who to hire.
- The provision for the act "right to explanation," that includes a set of legislation in the General Data Protection Regulation Act of European Union proposed in 2018 that deals with AI and data protection. In other words, people have the right to ask for the information they possess and how it is used.

## 5.1. Level of ethical AI

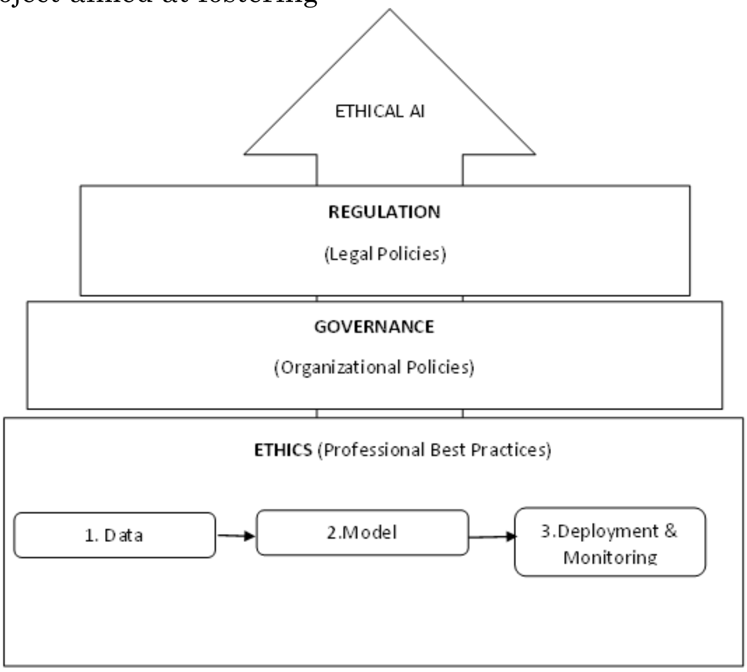


**Figure 2. Levels of Ethical AI**

The impact of various factors, including the professional behavior of developers and users, organizational governance of these individuals, and judicial oversight of both individuals and organizations, results in ethical AI. Second, there are three basic stages to the AI lifecycle, each of which must be finished before the subsequent step can start. These phases are as follows:

Data management includes the following steps:

i. Data collection,

ii. Best security measures used to protect data,

iii. Data cleaning (including pre-processing and augmentation as necessary), and

iv. Data reporting

An AI model is trained using a dataset, and its performance is then tested using test datasets, reported, and verified.

Stakeholder participation, user-centered design, and model deployment in the actual world are followed by updates, ongoing validation, supervision, and auditing.

## 6. DISCUSSION

The direction in which we might lessen the harmful effects is also important. Because artificial intelligence lacks the emotional intelligence necessary to assess societal impacts, political contexts, or cultural contexts, researchers from a variety of professions must examine distinct community complexes in order to reduce the possibility of biases in extraordinary scenarios. For instance, due to bias against race, Google's photo recognition programme mistakenly identified black humans as gorillas. Political and societal ramifications were also seen. We might need to revise our hypotheses since artificial intelligence is routine, just like it is in our everyday lives. We may create the structure for appropriate regulatory and a code-of-conduct that will supervise and control, transparency, liability, and responsibility by investigating and researching this topic.

Second, there is still another issue that needs our attention: how artificial intelligence makes decisions. Artificial intelligence needs to be able to justify its choices in terms of moral principles. But the adaptive nature of artificial intelligence presents a challenge. It's possible that the programmer won't be able to predict every decision that artificial intelligence will make during testing and in the future. Even while this might be the case, it might damage user confidence in the AI system. One vehicle that uses AI is the Tesla Model S. According to Pizaro, Figueroa, Lopez, et al., it features a system called Traffic-Aware Cruise Control (TACC) that causes it to hit with a van parked on a European highway, injuring the van's owner (2022). The owner had faith in the AI software and anticipated that the automobile would stop, but it did not act as intended.

From the outset, it would seem that Artificial Intelligence ethics is a science that reduces the likelihood of immoral outcomes in the Artificial Intelligence. Yet, a closer examination shows that this intuition is incorrect. It's true that there are a few worries, either from ethicists themselves or from the effects of their involvement in AI groups. These risks are connected to psychological problems with limited ethicality in the ethicists themselves, problems with how people react to (or disregard) ethical principles and advice, the difficult professional role of AI ethicists, the ineffectiveness of AI ethics guidelines, or the potential negative effects of ethics audits for AI products. So, this comment is not intended to downplay the importance of AI ethics. Instead, it seeks to enhance introspection and, thus, the discipline's efficacy. The comment also highlights how harder it is than it seems to put AI ethics into reality. It's possible for thoughtful ethical concerns to have unintended, unsuspected effects that, if judged independently, would be viewed as unethical. These undesirable results should be avoided in order to make AI ethics a discipline that can uphold its own standards.

## Conclusions

A recent technological development is artificial intelligence. It is widely used across many industries. In the end, it impacts human beings' principles, morality, and ethical ideals either directly or indirectly. Human dynamics and potential could be altered by artificial technologies. Prior to that, it is our social responsibility that we must establish criteria for AI decision-making accountability, openness in decision-making, data gathering privacy, and bias mitigation. Being human, we must confront these problems. Artificial intelligence technology can aid human decision-making even though it may be true that it cannot completely replace human judgement. To address effectively the moral and ethical concerns raised by artificial intelligence, a solid framework must be created.

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Stevan Didijer
1911-2004

# Narrowing the Marketing Capabilities Gap

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**ABSTRACT**

**Purpose:** In marketing discipline, there is considerable interest in understanding the relationship between diverse approaches of Market Knowledge Learning and Organizational Performance, and recently, how analytics and emerging revolutionary technologies are changing this relationship. To fully apprehend this relationship it is first necessary to uncover the role of Marketing Capabilities, the management mechanism that boosts Organizational Performance using Market Knowledge.

**Design/methodology/approach:** A new construct that embraces Analytics and Adaptive Capabilities approach (AAC) was developed to increase our comprehension of Marketing Capabilities mechanism using structural equation modeling and regressions.

**Findings:** The model has shown an indirect-only effect of AAC using Static Marketing Capabilities as a mediator narrowing the Marketing Capabilities Gap and avoiding any tautological capabilities pitfalls.

**Research limitations:** A deeper endogeneity test could be executed related to adaptive market approach as well it was an original preoccupation concerned to dynamics capabilities.

**Practical implications:** It enabled managers to understand what AAC are. Additionally the results suggest precaution for headhunter because AAC needs pre-existing marketing capabilities.

**Social implications:** It provides to managers a useful tool to assess their organizations regarding analytics in marketing realm, what makes it possible to compare with rivals and to predict the investments.

**Originality/value:** It lies in to appraise the Marketing Capabilities management mechanism and a step by step scale developed for AAC in different industries in Brazil.

**KEYWORDS**: Analytics Adaptive Capabilities. Scale development. Marketing Capabilities Gap

## 1. INTRODUCTION

According to the literature review of Barrales-Molina, Martínez-López, and Gázquez-Abad (2014) and Pereira & Bamel (2021), Marketing discipline increases attention in emerging revolutionary technologies of the recent data-driven decision-making scenario, in particular using the capabilities literature. To fully understand the learning and the outputs of Market Knowledge, it is first necessary to uncover the role of Marketing Capabilities and its management mechanism that allows the relationship between the new opportunities of Market Learning and Organizational Performance to exist.

The utilization of Big Data, mobile connectivity, e(m)-commerce, and the Internet of Things (IoT) has led to the emergence of revolutionary technologies that provide interactive and voluminous market information. This information is used as input to advanced analytical methods, transforming both structured and unstructured internal and external data into valuable Market Knowledge (Wedel & Kannan, 2016). These new opportunities for learning are at the forefront of recent and complex performance-driven debates surrounding emerging technologies and analytics (Chuang & Lin, 2017; Wamba et al., 2017; Donthu et al., 2021; Ahmed et al., 2022).

Revolutionary technologies have significantly improved the power of analytics, which has paved the way for the emergence of Adaptive Business Models such as experimental spin-offs, startups for industry foresight (Kiron, Prentice, & Ferguson, 2014), joint ventures, external networks, and collaborative strategies (Barrales-Molina, Martínez-López, & Gázquez-Abad, 2014). However, there is a significant literature gap in measuring the construct that represents learning capabilities related to analytics, which are used in conjunction with the adaptive approach explained in Day (2011). To address this gap, a scale for Analytics Adaptive Capabilities (AAC) has been proposed and tested as an antecedent variable to organizational performance (OP). However, the relationship between AAC and OP only exists with the mediation mechanism of Marketing Capabilities.

Also according to Barrales-Molina, Martínez-López, and Gázquez-Abad (2014) and Pereira & Bamel (2021), the integration of various marketing resources, capabilities, and processes into a common framework is hindered by the wide range of options available. This plethora of capabilities, often without clear construct content delimitation and scale validation, has led to conflicting and misleading findings regarding the nature and contributions of analytics for marketing.

While tautological research may sometimes yield positive results, it can also lead to pitfalls, such as testing correlations between similar dynamic capability scales. The present work has aimed to avoid such pitfalls by testing a new scale derived from adaptive capabilities (Day, 2011), which is an advancement related to dynamic capability.

Day (2011) differentiates between static marketing capabilities, which are stable capabilities, and dynamic marketing capabilities, which are capabilities that can be reconfigured and augmented, or as capabilities to pursue new opportunities.

In addition to the challenges related to capabilities, a multitude of recent empirical studies in Marketing and Information Systems have utilized various constructs related to analytics. These constructs include terms such as Business Analytics, Business Intelligence & Analytics (BI&A), Customer Relationship Management (CRM) Analytics, Social Media Analytics, and Big Data Analytics (Chuang & Lin, 2017; Côrte-Real, Oliveira, & Ruivo, 2017; Trainor, Andzulis, Rapp, & Agnihotri, 2014; Wamba et al., 2017).

It is important to recognize the potential pitfalls that may arise from an overemphasis on capabilities and analytics without adequate theory development. Such tautological pitfalls can occur when concepts are overused and applied without proper consideration for their underlying theoretical foundations.

The most prominent contribution of the present work is to uncover Static Marketing Capabilities mechanism between AAC and Organizational Performance. The step by step scale development of AAC and the association between this new construct to Organizational Performance was tested using Structured Equation Modeling (SEM) with Partial Least Square (PLS) and Ordinary Least Square (OLS) with SPSS PROCESS macro. In the next sections, we discuss some concepts and assumptions and after we propose the model and the new scale, and tested them. Synthetically, the paper showed an indirect only-mediation of Marketing Capabilities and discuss how to narrow the Marketing Capabilities Gap.

## LITERATURE REVIEW AND THEORETICAL DEVELOPMENT

The concept of absorptive capability (ACAP) is commonly used in traditional Marketing and Strategy literature to describe the overall learning process. This approach employs exploitative and explorative market orientation or responsive and proactive market orientation (Barrales-

Molina, Martínez-López, and Gázquez-Abad, 2014; Ozdemir, Kandemir, & Eng, 2017). While this literature is prominent, it falls short in addressing the role of analytics and relies heavily on traditional marketing methods and approaches (Wedel & Kannan, 2016), thus failing to close the marketing capabilities gap (Day, 2011).

To solve the lack of an AAC scale and test the mediation role of Marketing Capabilities we developed a new scale using the MacKenzie, Podsakoff, and Podsakoff (2011) validity framework have ten steps that were followed here and are outlined using the notation: (validity framework - step X). We followed this framework and used other scale quality tests.

Day (2011, 2014) criticize the current Resource-Based View literature, and even the current Dynamic Capabilities literature, as less dynamic theories than the market demands, suggesting the existence of the Adaptive Capabilities. Directed by the point of view of Day (2011, 2014) the present work advocate that AAC explore market opportunities. AAC reflect the **(AIQ) Analytical Information Quality**, and a **(TE) Team** exploits it with specific **Expertise** (analytical, technology, and business) improved by **(MKL) Market Knowledge Learning**. In summary, to develop a conceptual definition of the construct (validity framework - step 1), AAC can be classified as an Adaptive Capability that uses Analytics. Of course, this definition is based on two others, Adaptive Capability, and Analytics, defined in the present theoretical review.

Using MacKenzie, Podsakoff, and Podsakoff (2011) suggestions (validity framework - step 1), organizations are the AAC entity and the AAC general property are the capabilities of these organizations to use sophisticated data technology approach to boost a market openness in a continuously experimental behavior, forging partnerships, vigilantly for deep market insights. AAC is multidimensional, and its stability is across cases, where cases are, for example, projects of marketing, data science, R&D, or product/brand innovations.

In terms of dimensionality, AAC consists of three reflective first-order constructs. While information quality is a well-known and measured construct (Gorla, Somers, & Wong, 2010; Wieder & Ossimitz, 2015), it is important to note that emerging technologies handle data in novel ways, leading to an increase in **Analytical Information Quality**. Market data is no longer limited to information systems within databases but includes web and social media data, different types of data that are merged into data lakes or warehouses, and independent datasets such as texts, videos, and denormalized spreadsheets that are prepared for data science applications. The process of data engineering and cleansing gives rise to another type of data, which in turn leads to another type of information quality, which we refer to as Analytical Information Quality (Provost & Fawcett, 2013).

**Teams** with special **expertise** perform analytics. Updated quantitative studies provide empirical evidence that confirms the positive role developed by innovation teams (Barrales-Molina, Martínez-López, & Gázquez-Abad, 2014, Sincorá, Oliveira, Zanquetto-Filho, & Ladeira, 2018). Another example is a quantitative work executed with Chinese senior executives that identified exchange and integration of team knowledge, and by its turn, this improves the organizational financial performance because of new product development (Tseng & Lee, 2014).

Analytics can help in the **Market Knowledge Learning** (Barrales-Molina, Martínez-López, & Gázquez-Abad, 2014; Pereira & Bamel, 2021). Weaven et al. (2021) and Davenport (2006) exemplifies the market knowledge learning by saying that the organizations may spend many years accumulating data from different approaches before having enough information to analyze a marketing campaign in a trusting and efficient way. This market knowledge is all information that the organization has about the customer and his needs in different situations and various moments, past, present and future (Cooke & Zubcsek, 2017). AAC has a construct that responds to market accelerating velocity and complexity with a more outside-in and exploratory learning capability. This first-order construct is based on Absorptive Capability (ACAP) with the improvement of vigilant, experimental and, market openness of Day (2011).

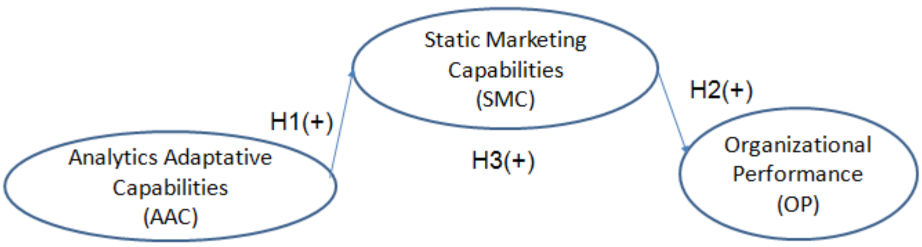
The first-order constructs do not have a causal relationship with AAC; instead, they represent the dimensions of the second-order construct. Another crucial point for defining the construct is the reflective/formative issue. It is essential to understand that whether a construct is reflective or formative is not inherent but a matter of definition (MacKenzie, Podsakoff, & Podsakoff, 2011). The three dimensions of AAC represent its manifestations. For instance, learning a new statistical method like clustering can enhance the team's expertise, which in turn can improve market knowledge learning and analytical information quality.

As part of the first step in the validity framework, which involves defining the construct, it is important to differentiate AAC from other constructs in the field of marketing capabilities (MacKenzie, Podsakoff, & Podsakoff, 2011). Figure 01 summarizes the position of AAC in relation to team expertise, which is utilized during the reconfiguration process of ACAP, and then passes through static marketing capabilities such as resource/capabilities related to customer lifecycle assessment, loyalty or churn programs, pricing, segmentation, and personalization.

## THEORETICAL MODEL AND HYPOTHESES DEVELOPMENT

Market knowledge is a crucial point of connection between the constructs discussed in this paper. The source of this knowledge can be diverse, ranging from CRM systems and social media to new technologies like IoT and big data. However, the way of learning remains the same, that is, by using quantitative evidence (Davenport, 2006). This evidence is then used to launch Adaptive Business Models, such as experimental spin-offs, industry foresight, and collaborative network strategies. The Theoretical Model is presented in Figure 01, and hypotheses are introduced in the following section.

**Figure 01 – Theoretical Model**




**Source: Prepared by the authors**

The Information System Literature has extensively used the concept of capabilities to explain the learning process (Popovič, Hackney, Coelho, & Jaklič, 2012; Teo, Nishant, & Koh, 2016; Wang & Byrd, 2017), but these approaches have not explicitly focused on the Market Knowledge learning process, which is crucial for changing/reconfiguring organizational strategies (Barrales-Molina, Martínez-López, & Gázquez-Abad, 2014). Therefore, the unique contribution of the present work lies in the utilization of Market Knowledge through AAC.

Some digital marketing technologies facilitate large-scale field experiments that produce market knowledge and become powerful tools for eliciting the causal effects of marketing actions (Wedel & Kannan, 2016). Examples are A/B tests and recommendation systems. The former started with changes in site colors for best sales, and nowadays they apply machine learning to test small details for full automated super individualized market-mix. By it turn, recommendation systems can interact directly with stock management or other Marketing capabilities like loyalty programs and Customer Relationship Management (CRM) building super segmentation approaches.

Complementary capabilities, idiosyncratic business needs, and organizational procedures\routines should be integrated by teams of technologists and scientists that leads with complex and sophisticated technological knowledge (Cohen & Levinthal, 1990). This seminal work about market information learning, before the discussions about analytics and big data boom (Ciampi et al., 2021), gives us a clue that technologies uphold the market knowledge impacting other marketing capabilities like pricing, segmentation, and personalization. From this discussion and the assumption about the capabilities tautological pitfall, the first hypothesis raises.

**H1. AAC has a direct positive effect on Static Marketing Capabilities.**

Marketing literature is concerned about the relationship between Marketing and performance constructs using Capabilities (Morgan, 2012; Kozlenkova, Samaha, & Palmatier, 2014) but few works measure Day's named "Static Marketing Capabilities" improvement in organizational performance (OP). OP is measured subjectively.

We assume the Marketing Capabilities importance for Performance, and the following hypothesis is declared to uncover the literature term avoidance:

**H2. Static Marketing Capabilities have a direct positive effect on Organizational Performance.**

Analytics can improve marketing capabilities/resources like customer lifecycle assessment, loyalty or churn programs, pricing, segmentation, and personalization (Germann, Lilien, Fiedler, & Kraus, 2014; Wedel & Kannan, 2016). However, these capabilities/resources need to have its preexisting procedures/routines to AAC make possible disruptions or become Adaptive Business Models like experimental spin-offs, industry foresight or collaborative network strategies.

Extant literature argument that CRM systems are enablers for Marketing Capabilities (Wang, Hu, & Hu, 2013; Barrales-Molina, Martínez-López, & Gázquez-Abad, 2014; Chatterjee, Chaudhuri, & Vrontis, 2022) which indicates the dependence of some technological capabilities to other sorts of capabilities. Additionally, the technology effectiveness, its output, is enabled by preexisting capabilities (Boulding, Staelin, Ehret, & Johnston, 2005; Ferreira & Coelho, 2020).

Finally, some Technology Capabilities Constructs about analytics are assumed to have a direct effect on Performance (Wamba et al., 2017; Ferreira & Coelho, 2020). On the other hand, Adaptive Capabilities constructs have no direct effect (Morgan, Zou, Vorhies, & Katsikeas, 2003). The results show a mixed behavior, and there is hardly clear evidence for a positive impact. In brief, AAC as a kind of technological Adaptive Capability depends on preexisting marketing capabilities to improve performance, and this is the reason to test the mediation and expect a not significant direct relationship to performance. Thus, we assume that AAC translates organizational performance just thru Marketing Capabilities. From this discussion, and using the Zhao, Lynch, and Chen (2010) terminology about mediation, we formulate our third and central hypothesis:

**H3. Static Marketing Capabilities have an indirect-only mediating role between the AAC and Organizational Performance**

The last hypothesis assumed the terminology of Zhao, Lynch, and Chen (2010) that detail three possibilities regard to mediation, (i) Complementary mediation, there are direct and indirect effects and both point at the same direction. (ii) Competitive mediation, there are direct and indirect effects, and they point in opposite directions. (iii) Indirect-only mediation, there is only the indirect effects.

## METHODOLOGY

A survey was executed to test the hypotheses (validity framework - step 5) with Brazilian users of Linkedin using a google docs form. It was sent after mining professionals employed (at least one year) and from the following profiles: Marketing Manager/ Analyst, Product/ Brand Manager/ Analyst, Marketing Research Manager/ Analyst, R&D Manager/ Analyst, Top Management, IT Manager/ Analyst, Innovation Manager/ Analyst, Data Analyst/ Scientist, Other Management Positions. The survey was conducted from December 2017 to March 2018, and garnered a total of 250 records for the purposes of scale validation and item purification, without any additional treatments (MacKenzie, Podsakoff, & Podsakoff, 2011). From this larger sample, a heuristic holdout sample of 200 was selected for use in step 6 of the analysis. Finally, a subsample of 195 respondents was used to validate the final model, after excluding those with IT profiles.

The AAC construct described earlier is new, and can´t be confused with the existing constructs related to Analytics which usually deal with greater technological detail (Rapp, Trainor, & Agnihotri, 2010; Wamba et al., 2017). Table 01 defines the dimensions of the three first-order AAC constructs and how to operationalize the multi-industry questionnaire.

In the validity framework, step 2 involves generating items for the AAC construct. These items are all new but were adapted from the literature review. The formal specification of the measurement model, without any formative indicators, is presented in Table 01 as part of the validity framework in step 4.

The Table 01 adaptation (i) was a change in the items that deal with data improvements due to a CRM implementation, so the new items address any data improvements. By it turn, the adaptation (ii) was necessary because the original scale did not encompass the Davenport (2006) concept of quantitative evidence in decision-making. This author explains this characteristic as a background for competing on analytics. Additionally, in the three questions of the original work of Chuang and Lin (2013) emphasis was given to the use of quantitative sources of information.

Regarding the Team Expertise, no other questionnaire tested concepts of quantitative evidence, market immersion, and experimentation, key parts of analytics and Day(2011) concepts. This idiosyncrasy came from the AAC contextualization as an Adaptive Capability discussed in the theoretical section.

The adaptation (iii) was necessary because projects can be done by teams especially formed for this purpose, at a strategic level of top management or even as a specific management initiative like marketing research, or innovation, IT, R&D, or product/brand management. The original scale assumes IT team only (Kim, Shin, & Kwon, 2012).

**Table 01** - AAC - Defining the first-order constructs

| Defining the Constructs | Source of the indicators |
|---|---|
| Analytical Information Quality – refers to the quality of Analytical information outputs | (i) Adaptation from Chuang and Lin(2013) scale |
| Team Expertise– Represents the professional abilities of the project team that are fundamental to perform tasks. (ex: skills or knowledge) of three different dimensions.<br><br>Dimension Analytical Expertise- for Holsapple, Lee-Post, and Pakath (2014) is about to give high priority to the resolution and recognition of problems based on quantitative evidence. This expertise has others characteristics like data-driven learning, and experimentation (Day, 2011).<br>Dimension Technological Expertise - represents the professional abilities of the project team (ex: skills or knowledge) that are considered fundamental to perform tasks related to programming languages, data engineering, and cleansing, etc. to improve Analytical Information Quality and learn Market Knowledge<br>Business Expertise - represents the professional abilities of the project team (ex: skills or knowledge) to perform tasks related to internal and external business understanding, and related to the capacity to collaborate inter and intra-organizations, all task driven by market immersion and openness looking for industry foresight, customer insights or collaborative networks (Day, 2011). | (ii) Dimension Analytical Expertise–New scale inspired in Popovič and others (2012) and Day (2011)<br>(iii.a) Dimension Technological Expertise–New scale inspired by Kim, Shin, and Kwon (2012)<br>(iii.b) Dimension Expertise in Business–New scale inspired by Kim, Shin, and Kwon (2012) and Day (2011) |
| Market Knowledge Learning - the ability of the team to recognize the value of new external knowledge, assimilate and apply that knowledge (Cohen & Levinthal, 1990). These authors argue that the ability for assessing and using external Information is, in most part, | Adaptation from Pavlou and Sawy, (2013) and Pavlou and Sawy, (2010) scales and influenced by Day (2011) |

| | |
|---|---|
| directed by the level of previous knowledge, what is related to analytical information quality. | |

**Source: Prepared by the authors**

The references for the other constructs are all based on established works in Marketing. The concept of Static Marketing Capabilities focuses on marketing competencies (Conant, Mokwa, & Varadarajan, 1990) and employs a multi-industry scale adapted from Song, Di Benedetto, and Nason (2007). In addition, Organizational Performance uses a scale reproduced from Jaworski and Kohli (1993) as it is challenging to obtain objective performance data in a cross-industry survey. Thus, this study measures performance subjectively.

Categorical data for multi-group analyses was based on organizational size and respondents' profile. The nonparametric equivalence analysis technique, Partial Least Square - Multi-Group Analysis (PLS-MGA), was used. This technique is considered an original extension of Henseler's (2009) MGA method. Despite hypothesis delimitation, control variables such as organizational size and respondents' profile were tested. The MGA results differentiated IT and non-IT respondents.

Aside organizational size and respondents profile, the work used only seven-point Likert scales, ranging from "totally disagree" (1) to "totally agree" (7). To test differences between early and late responders a PLS-MGA was used too, with no significant differences found. Another precaution was to assess common method bias using Harman's single-factor test (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

There is no missing data. According to checked non-normality, the empirical test of theoretical hypotheses was made using structural equation modeling (SEM) on SmartPLS software (version 3.2.4).

## RESULTS ANALYSIS

The univariate skewness and kurtosis, with values of 14 from 31 likert variables are out of interval from -1 to 1, indicate non-normality for the original sample, what was confirmed after executing the Shapiro-Wilks and Kolmogorov-Smirnov tests rejecting the hypothesis of normality for all 31 variables (Hair, Black, Babin, Anderson, & Tatham, 2009).

The scale purification and refinement (validity framework - step 6) resulted in the exclusion of two questions, as seen in Appendix I, due to cross-loadings tests. To gather data from new Sample (validity framework - step 7) a holdout with only 200 first registers of the original sample, we called as heuristic subsample, was used with no big difference (MacKenzie, Podsakoff, & Podsakoff, 2011). The holdout was used only to confirm refinement of step 6.

Some Multi-group Analyses was performed using organizational size and profile information. Using a data-driven approach, the SmartPLS suggested the following groups for size: (a) less than 10 employees, with 48 registers, (b) more than 1000 employees, with 52 registers, and (c) the middle, with 150 registers. The PLS-MGA and the Permutation algorithm were performed using the combination of these three size groups and two groups of profile resulting in p-values bigger than 0.05, i.e., rejecting the hypothesis of group differences about organizational size. However, for profiles assessment, the PLS-MGA shows differences from IT, 55 registers, and non-IT respondents, 195 registers (final sample), then just non-IT respondents were used as the final subsample (MacKenzie, Podsakoff, & Podsakoff, 2011) for model tests.

Using the validation/final subsample with MICOM process (Henseler, Ringle, & Sarstedt, 2016), we confirmed the possibility of pooling the data of the other profiles. Step 1, configural invariance assessment ensure that both setup and algorithm parameters of the measurement and the structural model are identical; we did no additional data treatment for each group, and algorithm settings are the same. For Step 2 (compositional invariance) and 3 (composites' equality of mean values and variances across groups) we used the permutation algorithm with 5000 permutations confirming no significance and then measure invariance.

The AAC construct has the biggest number of variables, 19 after the deletion of 2 items. Therefore, preliminary would be 190 respondents using the rule of thumb of 10 times (Hair, Hult, Ringle, & Sarstedt, 2017). Another conservative way, making a statistical power test in 95%, and assuming an f square of 15%, the software GPower determines, for a significance of 1%, the size of the sample as 170 respondents. The GPower statistical test chosen is one that tries to maximize the multiple regressions R square adding new predictors to the solution, $f^2$ (Faul et al., 2007). We used 4 predictors, including 2 control variables.

**Model tests**

The PLS algorithm was executed with the default values following the guidelines of Hair et al. (2017). All constructs have at least three variables and are reflective according to the content definition, or *a priori* specification.

The hierarchical components are treated using repeated indicators approach (Hair et al., 2017), and the results of the measurement model regarding the validity and reliability show Cronbach's alpha and composite reliability greater than 0.7 and AVE, greater than 0.5. Measured for the first-order and second-order AAC construct (MacKenzie, Podsakoff, & Podsakoff, 2011). The external loads of convergent validity are greater than 0.7 (validity framework - step 6).

Still on the measurement model was analyzed discriminant validity using the Fornell-Larcker criterion, according to which the square root of the AVE must be greater than the other constructs loads. After exclusion of two items, the cross-loading test showed no problem, confirming the validity at construct level (validity framework - step 6). Both tests were executed for multidimensional constructs of AAC (validity framework - step 8).

The structural model collinearity was evaluated using the VIF indicator, using less than 5 as a parameter, with the highest result being 4,097 (Hair et al., 2017). After, the coefficients are evaluated using the Bootstrapping procedure with 5000 subsamples with the option "no sigh changes" (validity framework - step 6). The coefficients are not significant (p-value <0.05) only for the statistical test of the relationship between AAC and Organizational Performance indicating an indirect-only mediation of Static Marketing Capabilities (H3).

For a more in-depth analysis (see Table 02 and Figure 02), the macro PROCESS of SPSS confirmed the H3, indirect-only effect for mediation, (a) and (b) <0.001 and (c´) not significant, and gave more information using Ordinary least squares (OLS) regression analysis with the latent scores outputted from smartPLS.

We used the procedures and parameters of Hayes (2013), and the results of the bootstrap with 10000 resample are summarized in Table 02 with results for R2, F statistics (degree of freedom 1 and 2) and p-values. It also includes unstandardized regression coefficients of direct paths (a, b, and c'), and the indirect path ab with significance level for bias-corrected 95% confidence intervals, and standard error(SE).

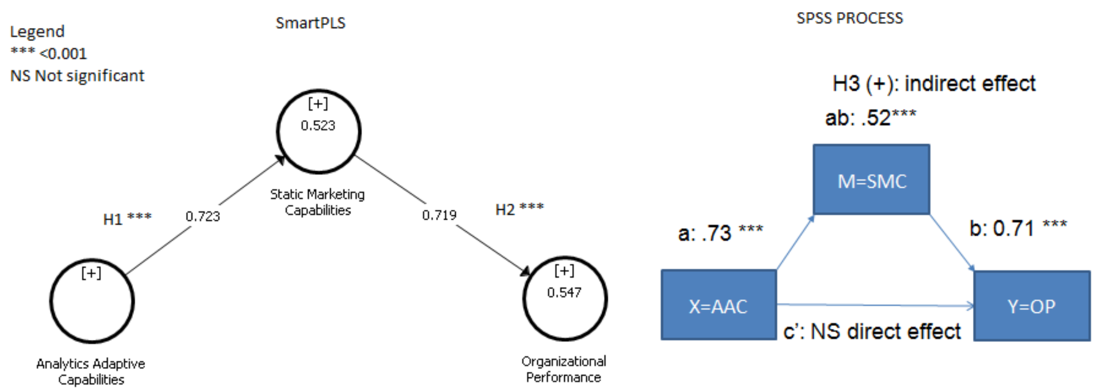
**Table 02** - PROCESS OLS mediation results

| | Consequent | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Antecedent** | M(Static Marketing Capabilities) | | | | Y(Performance) | | | |
| | | Coeff. | SE | *p* | | Coeff. | SE | *p* |
| X(AAC) | a | .7325 | .0640 | <.001 | c' | .0532 | .0859 | NS |
| M(Static Marketing Capabilities) | | -- | -- | -- | b | .7084 | .0865 | <.001 |
| Constant | i1 | .0 | .0494 | 1 | I2 | .0 | .0484 | 1 |
| | R2 = 0.536 p<.001 | | | | R2 = 0. 3273 p<.001 | | | |
| | F(1,193) = 130,8382 | | | | F(2,192) = 90,5057 | | | |

**Source: Prepared by the authors**

The first two hypothesis was confirmed (see Figure 02, left side), and they gave responses to extant literature and introduced AAC as an antecedent of the realm of Marketing Capabilities. About the main test, mediation (see Figure 02, right side), the indirect effect (ab) resulted in a value of .5189 using both the normal theory test and the bootstrap confidence interval (Hayes, 2013). As H3 is the main test, to improve the robustness of the indirect effect value, another test procedure was executed using a simulation-based method, Monte Carlo using the MCMED macro (Hayes, 2013). MCMED showed the same value with confidence intervals ranging from .3734 and .6811 (Preacher & Selig, 2012), i.e., not passing thru zero.

**Figure 02: SmartPLS algorithm and PROCESS SPSS outcomes**




**Source: Prepared by the authors**

Thus H3 was confirmed, no direct significant effect, using SEM and OLS indicating an indirect-only mediation between AAC and Organizational Performance, what agree with part of literature that we assumed as correct, what has a definite impact for practice and academics. The mediation effect is most important as higher is the indirect-effect value, not the inexistence of direct-effect (Zhao, Lynch, & Chen 2010), and have to be analyzed together with the size of the effect $f^2$, which evaluates if any omitted constructs generate substantive impact on the endogenous constructs. This caveat is necessary to avoid the epiphenomenal association, that means a mediator correlated with another omitted construct (Hayes, 2013), but f2 results deny this association as we will see.

The indirect-effect has a value of .5189, but it is a scale bound then it is dependent on the constructs metrics, and the measurement metrics in our model are not inherently meaningful because they are responses to rating scales aggregated over multiple questions (Hayes, 2013) and standardized by SmartPLS. Thus we used the R-squared mediation effect size (R-sq_med from PROCESS) that resulted in .3260, confidence intervals ranging from .1969 and .4546, meaning that AAC explains 32.6% of Organizational Performance valiance in our final sample, that has total effect larger than the indirect effect and they have the same sign, following the restriction of Hayes (2013) for R-sq_med effect size index.

Back to the SmartPLS, the $f^2$ effect shown that AAC on Static Marketing Capabilities and Static Marketing Capabilities on Organizational Performance are large, bigger than 0.35 (Hair et al., 2017), meaning the contribution of the exogenous construct for the $R^2$ of the endogenous construct. We also evaluated the coefficient of determination that measures the model predictive power. The result was 0.523 for Static Marketing Capabilities and 0.547 for Organizational Performance, with adjusted values of 0.521 and 0.543 respectively, which is considered both moderate (Hair et al., 2017).

The predictive relevance is evaluated using the Blindfolding algorithm with default configuration, omission distance equal to seven, resulting in a $Q^2$ that represents great relevance 0.377 (Organizational Performance) and near to great 0.318 (Static Marketing Capabilities), with 0.35 as parameters (Hair et al., 2017) using cross-validated redundancy (validity framework - step 9). To finish the validity framework - steps 6 and 9, with standardized root mean square residual (SRMR) fit parameter as less than 0.08 (Hair et al., 2017), was found a good fit of 0.064. In summary, the analysis of SEM carried out in SmartPLS, and OLS in

PROCESS resulted in the confirmation of all three hypothesis.

## DISCUSSIONS

The hypothesis H1 confirmed the importance of teams of technologists and scientists that leads with complex and sophisticated knowledge impacting in marketing capabilities (Cohen & Levinthal, 1990; Ciampi et al., 2021) with a moderated R square. By it turn, the hypothesis H2 confirmed the marketing capabilities literature (Morgan, 2012; Kozlenkova, Samaha, & Palmatier, 2014) and gives the possibility of using the term "static marketing capabilities". Additionally, H2 also resulted in a moderated R square for Organizational Performance. The parsimonious model empowers the moderated $R^2$.

The hypothesis H3 showed that AAC is dependent on Static Marketing Capabilities. This result gives to AAC the same enabler behavior of technological capabilities regarding preexisting marketing capabilities to improve performance (Barrales-Molina, Martínez-López, & Gázquez-Abad, 2014; Pereira & Bamel, 2021). These tests expand the knowledge of managers and academics. In particular to both profiles that take for granted the importance of analytics and think about it naively.

## CONCLUSIONS

The present paper helps to explain organizations that continually feel and act upon the emerging technological trends using a market knowledge with the adaptive approach. The paper shows that to improve Organizational Performance using AAC it is needed static marketing capabilities. Thus, analytics can boost traditional methods of customer lifecycle assessment, loyalty or churn programs, pricing, segmentation, personalization, which by its turns, can launch adaptive Business Models like experimental spin-offs, startups for industry foresight, they can promote joint ventures or external networks and collaborative strategies.

The results show findings both from academic and practice point of views. The academic relevance is to show how AAC acts through static marketing capabilities to become a critical and predictive element for organizational performance. Thus, the results of the research contributed to clarify the way in which the construct operates, additionally the paper escape from traps linked to tautological Dynamic Capabilities research.

Regarding the managerial context, this research effort enabled managers to understand what the Analytics Adaptive Capabilities are, as well as the static marketing capabilities that need to be developed and articulated by work teams involved in marketing activities. The expertise of these teams are used to recognize the value of new market knowledge through the use of technologies, assimilating them and applying them to new adaptive business models. Thus, AAC is a rare, valuable and adaptable capability to the market demands.

The paper provides to managers a useful tool to assess their organizations regarding AAC, what makes it possible to compare with rivals and to predict the investments to improve AAC dimensions. In particular, we highlight the new Analytical Information Quality that is different from the widespread Information Quality construct.

A limitation is that the idea of researching the adaptive market approach is not entirely new, another limitation it that deeper endogeneity test could be executed related to adaptive market approach as well it was an original preoccupation concerned to dynamics capabilities. However, as an academic contribution, the results and discussions on marketing capabilities seem to expand the field toward the emerging revolutionary technologies. For management, these results suggest precaution for headhunter because AAC needs pre-existing marketing capabilities and sometimes a step back is necessary.

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