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A data-driven decision-making readiness assessment model: The case of a Swedish food manufacturer

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ABSTRACT

This study proposes a model to assess data-driven decision-making (DDDM) readiness in organizations. We present the results from investigating the DDDM readiness of a Swedish organization in the food industry. We designed and developed a questionnaire to collect data about the organization's decision-making and IT systems. We conducted eleven interviews at the case study organization: ten with various functional decision-makers and one with the IT Manager about IT systems. The interview data were then analyzed against known decision theories and state-of-the-art DDDM. Based on the interview outcomes, we analyze the data according to the assessment model and recommend changes to the organization's readiness for data-driven decisions. The findings show that while the organization was assessed as ready in the decision-making process and decision-maker pillars, it was not ready in the data or analytics pillars. Accordingly, we recommend a set of actions, including considering integration and decision systems, further developing dashboards, increasing data and analytics resources (such as enterprise data warehouse, big data management tools, data lake environment, and data analytics algorithms), and defining key roles necessary for digitalization and DDDM (such as Data Engineer, Data Scientist, Business Intelligence Specialist, Chief Data Officer, and Data Warehouse Designer/Administrator). The contribution of this study is the DDDM readiness assessment model, accompanied by a questionnaire for determining the readiness level in organizations.

1. Introduction

Within academic disciplines and practice, data and analytics have become among the most promising and relevant competitive factors for businesses [1]. Many successes and failures of organizations throughout the years have been attributed to a single, fate-changing decision. Massive pressure has thus been placed upon decision-makers to ensure that the best decision is made in a correct and timely manner [2]. This has resulted in extensive research in decision-making and decision theory, evolving to encompass data-driven decision-making (DDDM), or making decisions based on the results and evidence provided by analytics, accommodating for the advancements in data science, machine learning, and analytics [3]. Based on a continuously increased availability of various forms of data and data sources, insights and findings can be derived objectively by using machine learning algorithms and data models, thus leading to DDDM which is more consistent in various different decision-making situations [4]. Such approaches are associated with superior decision-making, resulting in several benefits, like increased firm performance and the identification of new and valuable business opportunities [5,6].

From a terminological point of view, it must be distinguished between *data-informed*, *data-driven* and *data-centric*. *Data-informed* indicates little usage of data, in the sense that an organization systematically collects and stores data and decision-makers are principally aware of that data. However, data are not the main driver within decision-making processes [7]. *Data-driven* additionally includes that there are experts guiding the data organization process but, more importantly, these experts organize the analysis of such data, based on advanced technologies and in relation to the needs of decision-makers. Moreover, data-driven requires that intense use of data in decision-making is accepted and implemented company-wide across the various hierarchical levels [7,8]. Big data and big data analytics are key components of data-drivenness [9]. Finally, *data-centric* refers to organizations whose business model is based on data, and data itself is part of the value creation process within products or services [7], such as Google.

However, despite the growing amount of data, tools, and insights, decision-makers are still not fully benefiting from the capabilities of current technologies, especially without clearly defined guidelines and processes [10]. While the decision-making approaches, methods, and theories of renowned scholars, such as Herbert Simon and Henry Mintzberg, are still withstanding, every era requires the addition of

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modern approaches and practices to support environmental changes and technological advancements.

Current research highlights the importance of business intelligence, analytics, and data-driven insights for decision-making [11], and the potential of DDDM in generating dramatic improvements in firm performance [12]. However, an entirely DDDM process remains far from meeting expectations [13] and there is a gap in the literature that empirically explores the prerequisites of DDDM for enhancing decision-making quality [11] and the requirements for organizations to be deemed "ready" for DDDM.

Accordingly, the purpose of this research is to understand how organizations make decisions and therefore assess their readiness for DDDM. This will be undertaken in relation to the relevant literature to develop a solid understanding which accommodates for the capabilities of data-driven decision-making by integrating the classical decision-making elements with the modern advancements in big data and data analytics.

The empirical part is based on interviews with decision-makers at a Swedish food manufacturer. Based on the interview outcomes, we elucidate the as-is situation and recommend the to-be changes pertaining to their readiness for data-driven decisions.

We strongly believe that a classical approach to making decisions might not be enough in certain occasions where sheer amounts of data are available. A more contemporary decision-making approach is required in the age of big data. We advocate a decision-making approach of five pillars: data, decision, decision-maker, process, and analytics. In this report, we study those five pillars in a case organization via conducting interviews with decision-makers at the organization in order to gain a better understanding of their decision-making approach and potential, and accordingly be able to make recommendations to advance the decision quality further at the organizational level.

2. Decision theory for data-driven decision-making

Decision theory is a complex subject of debate that revolves around decision-making. Such theories have either evolved, developed, and changed to accommodate new advancements, or been disproved throughout many decades of interdisciplinary research [14]. Decision theory generally focused on rational decision-making [15]. It is a systematic study of the goal-directed and presumably non-random behaviors and actions of decision-makers, under events or conditions when different options or courses of action can be chosen [14,15]. Hence, the decision problem arises when a decision-maker must choose from a set of alternative acts, which are affected by events taking place in the environment, outside of the decision-maker's control. These actions result in various outcomes with positive or negative payoffs [15], which are usually the focus of decision theory, judged by pre-determined criteria or means-ends rationality (Hansson, 2014).

There are two main types of decision theories: normative and descriptive. Normative decision theory seeks to prescribe what decision-makers ought to rationally do [15], and the prerequisites which should exist for rational decision-making [14], whether or not such rationality is unfounded or unrealistic. On the other hand, descriptive decision theory explains and predicts how people actually make decisions in real life, which can be both rational or non-rational [15,16]. Thus, descriptive and normative decision theories are two separate, but possibly interrelating fields [15].

As technology advances and artificial intelligence (AI) becomes more prevalent, research has aimed to extend the principles of classical decision theory, along with information theory, game theory, and systems theory, in order to apply them to the decision-making processes of AI agents and machines, and study how they can be "trained" or "taught" to "decide" [3]. As far back as the mid-1900s, Simon believed that human thinking and information processing programs shared similarities in their ability to scan data for patterns, store them in memory, and apply them to make inferences. This has led to programs that can replicate or even exceed human decision-making and problem-solving abilities [17]. Nowadays, new research has even attempted to "mimic" human decision-making by training cognitive digital clones that can autonomously represent or augment human decision-makers [18].

Despite the many advancements in AI, the traditional tools of decision theory have not proven to be sufficient for automating decision-making, especially in complex and unpredictable scenarios with changing assumptions or preferences [3]. Accordingly, a growing interest in qualitative decision theories has arisen, which provide better support for automation through the development of hybrid representations and procedures that enhance quantitative decision theory's ability to address a wider range of decision-making tasks [19].

In this paper, we adopt the claims of DECAS (theory encompassing the **D**ecision-making process, d**E**cision maker, de**C**ision, d**A**ta, and analytic**S**) as a decision theory [3] that claims there are five main elements necessary for modern decision making. The three main elements focused on in classical decision-making research are: the decision-maker, the decision, and the decision-making process [20]. However, we strongly believe there exist two contemporary elements to make up the five necessary elements of a modern decision-making theory; those are data and analytics. Fig. 1 depicts these five elements, which are described in more detail in the following sections.

2.1. Decision-maker

The decision-maker applies the decision-making process to reach a decision and should have full and current information [21]. However, decision-makers do not possess complete control over the environment or their mental capabilities, and hence, as argued by Simon, cannot be rational. Thus, with or without the aid of computers, limitations of human rationality and calculation will persist due to the complexity of the world and the constraints of human computational capabilities [22], leading to a "bounded rationality" [23]. This leads to decision-makers selecting the first satisfactory solution rather than striving for an unrealistic, and potentially useless, optimal one. Additionally, Simon challenged the assumptions of decision theory that decision-makers always have a precise understanding of the problem at hand. Decision-makers often lack a clear idea of their problem and cannot always formulate it as an effectiveness or efficiency problem. In reality, problems are often better formulated as a search for a satisfying compromise, and finding a solution is always constrained by time and available resources. It is therefore up to the decision-maker to be able to use any decision-making process depending on the situation and available resources [22].

Moreover, the classical theory assumes that decision-makers choose from a set of fixed, known, alternatives with known consequences. This is an inaccurate assumption, as alternatives must often be sought, and the determination of consequences is a complicated, if even possible, task. Additionally, the decision-maker's information about the environment is typically much less than an approximation of the actual state [24].

Computers are thus capable of supporting decision-makers in problem-solving and exhibiting "intelligence", or behavior, that aligns with the goal and adapts to the environment. Intelligence allows the limited processing capacity of the (human or machine) decision-maker to utilize efficient search procedures in order to generate possible solutions [17]. Simon [24] claimed in the mid-1900s, that if the decision premises can be translated into computer terminology, then the digital computer can provide decision-makers with an instrument for simulating complex human decision processes. Nowadays, technological advancements have made such simulations possible for supporting and augmenting the cognitive processes of human decision-makers [18].

2.2. Decision

Due to the bounded rationality of the decision-maker, and the limitations in cognitive abilities and external factors, the optimal decision

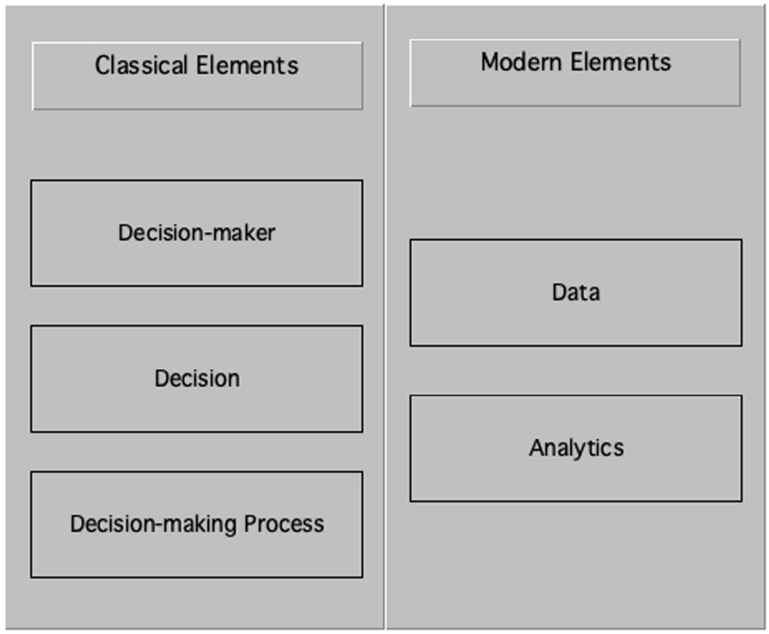

Fig. 1. Elements of modern decision-making theory.

cannot be reached. As a result, decision makers tend to "satisfice" by constructing a simplified model of rationality that takes into account the surrounding limitations and enables them to make a satisfactory or good enough decision [20,22]. Nevertheless, research continues to explore ways to approach the so far unattainable "optimal" decision.

An important characteristic of the decision is its quality, which includes timeliness, accuracy, correctness, and, in the case of quantitative decisions, validity and reliability. Data quality and the process by which it is collected and processed also play a crucial role in decision quality [25].

Advancements in technology have significantly transformed the ways decisions are made. While decisions used to rely solely on human cognition, they now utilize computers, systems, machines, analytics, and algorithms. Thus, decisions have inevitably changed. To keep up with these changes, research must redefine and explain the role of AI in decision-making and its impact on decisions and their outcomes, as well as understand the critical factors that influence the success of data-driven decisions [26].

2.3. Decision-making process

Simon proposed a structured and sequential decision-making process that involves: intelligence, or gathering data and information related to the decision, design, or analyzing the alternatives to determine outcomes and how they will meet the goals, choice, or selecting from the alternatives, and review, or implementation. Good choices are more difficult to make if either of the intelligence or design phases are neglected [20].

Drucker [27] also emphasized a structured decision-making process with clearly defined elements. These steps include problem classification, problem definition, determining the specifications which must be satisfied, making the right decision rather than an acceptable one to meet the boundary conditions, action planning, and finally decision feedback, which tests its validity and effectiveness against the actual course of events.

Unstructured decisions, on the other hand, are those that have not previously been encountered and lack a predetermined and explicit set of ordered responses [28]. While decision-making is often thought of as a linear process, Mintzberg and Westley [29] argued that it is actually iterative and identified it as follows: define, diagnose, design, decide. When decision problems are vague, uncertain, and fuzzy, or there is no pre-defined process or optimal solution, human intuition, experience, and judgement can be the basis for decision-making. Thus, decision-making is not always a clearly defined process and can involve a combination of data, experience, and feeling [28].

2.4. Data

Big data generally refers to data that is so large, diverse, and rapidly changing the it requires specialized technical architectures, analytics, and tools, and processes in order to create, store, manipulate and manage the data, and enable insights that reveal hidden knowledge and create business value [30,31]. However, generating business value from big data is a complex and dynamic process which involves various sociotechnical factors and value-creating mechanisms [32].

Three main features characterize big data: volume, variety, and velocity (aka the three V's). The volume of the data is its size or amount, and how enormous it is. Data volume is the primary attribute of big data and poses many challenges. Big data can be quantified by size in terabytes (TBs) or petabytes (PBs), as well as the number of records, transactions, tables, or files. Velocity refers to the rate with which data is changing, or how often it is created, generated, or delivered, such as streaming data from websites [31]. Here, the challenge is to be able to manage the data effectively and in real-time, or near real-time [30]. Variety includes the heterogeneity of data and its types, as well as the different kinds of uses and ways of analyzing the data in a holistic manner to derive insights. Data comes from a variety of sources, such as IoT data, logs, clickstreams, and social media. This means that common structured data is accompanied by unstructured data, such as text and human language, and semi-structured data, such as extensible markup language (XML), JSON or rich site summary (RSS) feeds. Furthermore, multi-dimensional data can be drawn from a data warehouse to add historic context to big data. Finally, the addition of a fourth V, veracity, focuses on the quality of the data and how trustworthy it is since the data can be collected from multiple sources which may include low-quality or noisy samples. Accordingly, it characterizes the quality as either good, bad, or undefined due to data inconsistency, incompleteness, ambiguity, latency, deception, or approximations [30,33].

While utilizing big data allows organizations to add value in the information value chain and support decision-making in various business areas [34], acquiring the data for the decision requires a good understanding of the domain (or business context) as well as the data itself. Therefore, datasets should be described in terms of the: required data to be defined, background about the data, list of data sources, method of acquisition or extraction for each data source, and problems encountered in data acquisition or extraction. Significant developments in data storage technologies at low costs allow organizations to produce and collect vast amounts of data [34]. However, on one hand, there exists too much data while, on the other hand, all acquisition requires time, effort, resources, and tools and systems for creating capturing, and delivering value from the data. Hence, the selection and acquisition of data by decision-makers might be due to personal preference, technical abilities, or streetlight effect, which is the tendency to rely on data that is "available" instead of data that is "needed" [35].

For example, most experiments and data-analytic research relies on data made available from some of the biggest data-driven companies, such as Facebook, X (formerly Twitter), Google, LinkedIn, and Amazon. However, such data may be biased towards solving those companies' problems, and not necessarily solving the grand problems which naturally face other organizations. Since researchers are limited to analyzing existing data, many are tempted not to formulate clear research questions or problems that enable them to define what data needs to be acquired. Consequently, the range of insights that could be generated remains unconsciously limited [31].

2.5. Analytics

The interest in analytics has been growing, and Google's adoption of MapReduce played a significant role in leading to many developments in the area of analytics. Furthermore, the development and deployment of tools such Apache Hadoop, SPARK, and Mahout has provided organizations with the ability to process extremely large datasets, which had not previously been possible. Analytics involves using advanced techniques, mostly machine learning and statistical, to find (hidden) patterns in (big) data. Most of such data, however, is not structured in a way so as to be stored and/or processed in traditional database management systems (DBMS). This calls for big data analytics (BDA) techniques in order to make sense of such data, which includes the integration and analysis of large amounts of heterogeneous data [30,31]).

During the IEEE 2006 International Conference on Data Mining (ICDM), the top-ten data mining algorithms, that could be used for analytics, were defined based on expert nominations, citation counts, and a community survey. In order, those algorithms are: C4.5, k-means, support vector machine (SVM), Apriori, expectation maximization (EM), PageRank, AdaBoost, k-nearest neighbors (kNN), Naïve Bayes, and CART. These algorithms cover classification, clustering, regression, association analysis, and network analysis for providing insights [31].

Based on the questions analytics aims to answer, it can be categorized mainly into descriptive, predictive, and prescriptive analytics which can jointly be used to support DDDM [36]. Descriptive analytics allow decision-makers to answer the question of "what happened?" based on historical data, and understand past and current decisions. Predictive and prescriptive analytics provide more sophistication by focusing on what might happen next and providing optimal behaviors and actions [30,32].

Nevertheless, analytics may mostly be used with the intention to predict. Prediction allows foreseeing the future by applying certain techniques on datasets and extrapolating relationships to provide forecasts. Predictive analytics is a process which extracts information from various data sources and utilizes it to elucidate patterns, as well as predict the future. It thus has the potential to bring great business value to organizations and individuals equally, and can be used by organizations to assess business risks, decide when maintenance is required, and anticipate market patterns. Added to that, prediction has been identified as a key research area of the future [30,31,36].

3. Research design and method

3.1. Problematization

The purpose of this research study is to assess the readiness of organizations for DDDM. Towards that end, we collect data about the different structures within an organization in order to assess their readiness. Additionally, less-ready functions/departments are provided with a recommended list of actions in order to help them become ready for the goal of DDDM and make decisions based on evidence from data and analytics algorithms. The research will provide a readiness index to the different departments/functions at an organization and classify structures in an organization into:

- Ready
- Almost ready
- Not ready

The readiness level will be based on the five elements of DDDM: data, analytics, decision-maker, decision, and decision process.

3.2. Research question

Accordingly, we seek to obtain an answer to the following question: "*how to assess the readiness of organizations for DDDM?*" In order for us to answer the question, we adopt a qualitative case study research approach.

3.3. Research methodology

A case study research approach is adopted to study the readiness of organizations towards DDDM in real-life context. Case study research is appropriate when the topic of interest is contemporary [37] and relevant research and theory are in their early stages [38]. Case study research is suitable to investigate "how" research questions, and is therefore used in our research [39]. The purpose is to explore decision-making at a real-life case organization, with attention to the elements of the decision-making theory explained in previous sections. Thus, we conduct interviews with decision-makers to investigate the different aspects of the decision-making process, and in doing so explore and describe the elements of the decision-making theory.

3.4. About the case study company

The food industry is an integral part of the international economy and plays a serious role in the provision of the necessities for human survival. Additionally, the global food system is still encountering serious challenges such as the increase of world population, rapid urbanization, aging of populations, sustainability, and recently the disruption to food logistics, for example, because of the war in Ukraine. Likewise, the fragmented nature of global food supply chains presents an additional challenge in responding to consumer requirements in terms of food safety, quality, and authenticity [40]. The advancements in decision science have deemed the conventional ways of making decisions obsolete and call for innovative approaches to making decisions. Henceforth arises the need for DDDM. Today, technology is a critical enabler, and food manufacturers could use technology to enable quality decisions to be made with the ultimate goal of providing quality food products to consumers.

Decision theory offers new opportunities for food manufacturers to address ever-increasing competition, emerging risks, and operational challenges. While data science denotes the analytics of multiple datasets, which come from both internal and external sources and are inherently complex, using AI algorithms supports DDDM following a process. Nowadays, the integration of both internal and external data has become the new normal in big data analytics. Internal data are often inadequate to address some challenges, such as customer profiling, new product development, and market expansion. DDDM in the food ecosystem is gaining traction to catch up with other areas which have achieved higher maturity such as retail, banking, and telecommunications.

This research project is about the readiness assessment of a Swedish food manufacturer for DDDM. In order to preserve their identity, the company will be referred to as *Food Co*. *Food Co* is a family business which was established in Sweden. *Food Co* is one of the largest food manufacturers in Sweden and the Nordic area. The reason this company was selected is attributable to the fact that they were at the beginning of their digitalization journey where DDDM was amongst the objectives they wished to achieve. However, they were unsure as to whether they were ready for DDDM and what areas needed development.

3.5. Collecting and analyzing the data

We collect data via interviews with decision-makers of the case study organization. The interview data is analyzed following a qualitative approach. Interviews are a part of interpretive research studies as a key way of accessing the interpretations of informants in the field. During the interviews, we follow the recommendation by Walsham [39] pertaining to the need to maintain good timekeeping during an interview, and the important balance between passivity and over-direction. Surveys are used as a data source since survey data are perfectly valid inputs for an interpretive study [39].

4. Applying the data-driven decision-making readiness assessment model in the case of Food Co

4.1. DECAS as a reference theoretical foundation for the model

In this paper, we adopt DECAS as a reference theoretical foundation [3]. According to the theory, decisions have always been a crucial topic in research. While there are many classical theories, decision-making needs to evolve to incorporate new technologies such as big data, analytics, machine learning, and automated decisions. Nowadays, decision processes have evolved, the role of humans as decision-makers has changed to become more intertwined with the support of machines, and data has become more abundant than ever. Such developments require new theories to support new phenomena, and DECAS represents a modern data-driven decision theory which aims to support the elements of data-driven decisions. The theory extends upon classical decision theory by proposing three main claims: the (big) data and analytics should be considered as separate elements along with the decision-making process, the decision-maker, and the decision; the appropriate collaboration between the decision-maker and the analytics (machine) can result in a "collaborative rationality", extending beyond the bounded rationality of each individually; and finally, the proper integration of the five elements, and the correct selection of data and analytics, can lead to more informed, and possibly better, decisions [3].

Accordingly, each DECAS pillar (aka element) will be assessed and a readiness score from "not ready", "almost ready", or "ready" will be respectively assigned according to their readiness (Fig. 2). Based on all five element evaluations, a general readiness evaluation can be identified for the organizational units involved in the study.

This score will show an overall readiness of the organizational unit with regards to DDDM adoption according to the following meaning (See Appendix C, Fig. 4):

– *Not Ready*

1. *Decision-maker* > Unaware of the decision-making theory, domain, practices, and technology. Lack of sufficient knowledge and awareness of the use of data and analytics algorithms. Both individual and group decisions are not clearly defined, nor when to take each.
2. *Process* > No clear decision-making process, neither for individual nor group decisions.
3. *Decision* > No clear understanding of the type of decisions. No link between decisions and problems or opportunities. Decisions are not consistent with corporate culture or known values. No learning from historical decisions exists.
4. *Data* > No clear use of data towards decision-making. That could be due to lack of data, lack of technology, lack of resources, or a combination thereof.
5. *Analytics* > No clear use of analytics algorithms in decision-making. That could be due to lack of knowledge, lack of technology, lack of organizational mandate, or a combination thereof.

– *Almost Ready*

1. *Decision-maker* > Awareness of some aspects of the decision-making theory, domain, practices, and technology. Some knowledge and awareness of the use of data and analytics algorithms. Decisions are mostly individual and lack group synergy.
2. *Process* > Process exists, but is sometimes in use and sometimes not. Process exhibits overruns, mostly in association with group decisions.
3. *Decision* > Some understanding of the types of decisions exists. Link sometimes exists between decisions and problems or opportunities. Decisions are not always consistent with the corporate culture and known values. Learning from historical decisions is not always active, but there is an attempt or plan.
4. *Data* > Data is partially and/or sometimes used in support of decision-making. That could be due to lack of data, lack of technology, lack of resources, or a combination thereof.
5. Analytics > Traces of the use of analytics algorithms in decision-making exist, but are not consistent nor systematic. That could be due to lack of knowledge, lack of technology, lack of organizational mandate, or a combination thereof.

– *Ready*

1. *Decision-maker* > Awareness of major aspects of the decision-making theory, domain, practices, and technology. Knowledge and awareness of the use of data and analytics algorithms. Decisions can be made individually and in a group.
2. *Process* > Process exists, and is in use. Time is acceptable either for individual or group decisions.
3. *Decision* > Clear understanding of the types of decisions. Link exists between decisions and problems or opportunities. Decisions are consistent with the corporate culture and known values. Learning from historical decisions exists.
4. *Data* > Data is ready and (often) used in support of the decision-making process. Appropriate technology exists, resources support the use and the environment.
5. *Analytics* > Re-current use of analytics algorithms in decision-making. Appropriate technology exists, resources support the use and the environment.

In terms of the actions recommended for each readiness level, they are explained below (See Appendix D, Fig. 5):

• *Not Ready*

 – *Actions*> Investment is required across all elements which are not ready! Including, decision-makers' knowledge transfer; data readiness via technology and resources; analytics readiness via technology and resources.

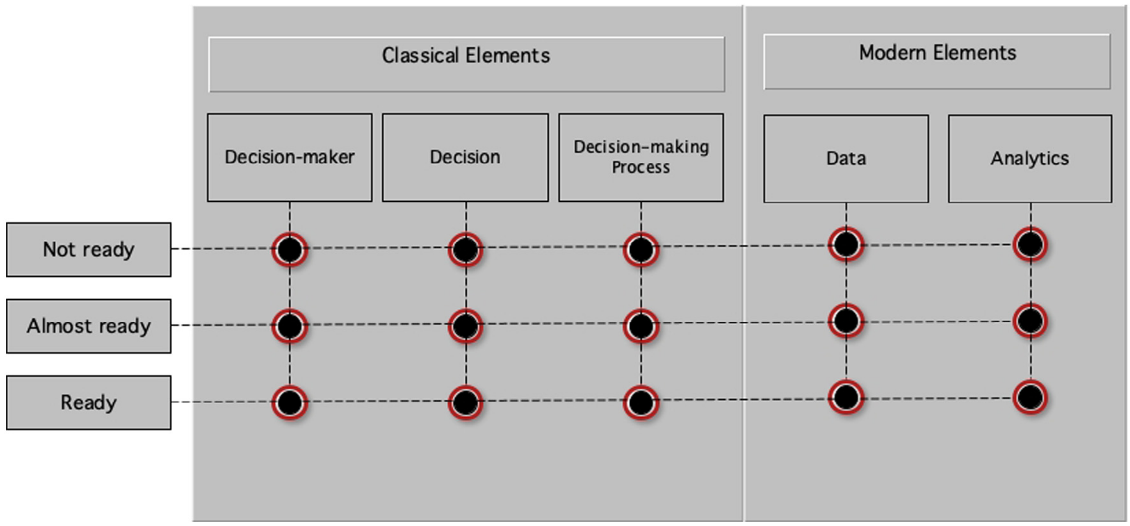

Fig. 2. Data-Driven decision-making readiness assessment model with the 5 pillars of DECAS.

- *Almost Ready*
  - *Actions*> Getting the elements which are not ready to a ready state, including: decision-maker knowledge transfer (e.g., analytics for decision making); data readiness via technology and resources (e.g., enterprise data warehouse, data mart, sandbox, data lake); analytics readiness via technology and resources (e.g., machine learning library, data mining tool, visualization analytics).
- *Ready*
  - *Actions*> Design, development, and use of a DDD platform. Followed by measurement of impact.

4.2. Data collection questionnaire

In this study, and in order for the researchers to be able to assess the readiness level of the various organizational units, a questionnaire was designed and used. The questionnaire, see Appendix [A], asks respondents 24 questions. The mapping of the questions to the five pillars of DECAS is explained in Table 1.

4.3. Conducting the interviews

To achieve the study goals, the below table shows the interview schedule with the decision-makers. All ten interviews were successfully conducted. The total time spent was a little over 11 h of interviewing time, since each interview lasted for approximately one hour. It is to be noted that the interviewees' names were taken off in Table 2 for privacy-preservation.

In total, the researchers have conducted 11 interviews, 10 decision-maker interviews (as per the above table) and one IT systems interview.

4.3.1. A note on verification

During the interviews, the researchers presented the questionnaire and typed in all the answers so that respondents could see and, whenever possible, correct or comment on what had been written. In two interviews, which were conducted in Swedish, the answers were translated into English and sent out to respondents for confirmation. Minor changes were applied, accordingly.

4.3.2. Inter-rater reliability

In addition to the previously noted verification, another mechanism was used to verify the analysis results. That is, inter-rater reliability. According to this, a high degree of agreement is sought amongst raters. Interview responses have consistently been close between raters, which showed a high degree of inter-rater reliability. On some occasions, differences were raised during the interview, and conversion was reached between raters, accordingly.

5. Results

5.1. Qualitative findings of decision-making interviews

In this section, we analyze the responses obtained from the ten different respondents as per the five pillars of DECAS. The results are summarized in Table 3.

Fig. 3 shows the DDDM readiness scores for each of the five pillars in the organizational units. Accordingly, the study revealed:

1. A high-degree of consistency was found between the different organizational units. That is considered to be a healthy organizational phenomenon;
2. Clear values have been consistently detected throughout the interviews, specifically: cost-efficiency, human-value, and sustainability;
3. The two pillars, or elements, of the decision theory which are found to be *ready* in all the organizational units are the *decision-maker* and the *decision process;*
4. The one pillar, which is found to be *almost ready* in all the organizational units is the *decision;*
5. There exist two pillars that are *not ready*! Those are: *data* and *analytics*. The analytics are not ready in any of the organizational units. The data is almost ready only in three out of the ten units: HR, Marketing, and Sustainability. However, even in those units, there are still data aspects missing, such as latency and structure, integration, and internal tools. Many of the units particularly lack external data. Such findings are also supported by the IT systems interview below, which revealed the same conclusion. This finding particularly contributes to current research by accentuating that an entirely DDDM process remains far from meeting expectations [13] largely due to deficiencies in the data and analytics pillars;

Table 1
Interview questions mapping to the five pillars of DECAS.

Question	***DECAS Pillars*** *Decision [6]*	*Decision-maker [5]*	*Process [4]*	*Data [3]*	*Analytics [4]*	***Mapping rationale***
What do you make decisions about? Which decisions do you make on an hourly, daily, weekly etc. basis?						Decision areas and their frequencies
How do you know what the correct decision is? Who decides on correctness? Which metrics to use to describe a decision as correct or incorrect? What to do if metrics are contradicting? Whom to consult on evaluating decision correctness?						Decision evaluation
Do you have an accuracy model for your historical decisions? The percent of FP & FN?						Historical decisions
Do you analyze errors? How does the analysis feedback the next decisions?						Decision quality and feedback
What VALUES to cater for the most in order to evaluate your decisions? Is it monetary e.g., cost/benefit analysis? Or social e.g., saving peoples' lives? What happens if there is contradiction between values?						Decision values
Is there any decision that you would like to be able to do, but cannot? What is the reason for that? How do you handle that situation?						Decision scope
How many decisions do you usually take a(n) hour/day/week/month?						Decision-maker capacity
Who makes the decisions? Is it a single person? Or hierarchy where one approves the others? Are there levels or is the decision being made at a single level? Are they planned or unplanned? Is there a decision-making structure?						Decision-maker structure
Who bears the consequences of making wrong decisions? The question is about accountability						Decision-maker accountability
What is the description of TIME as an important decision-making aspect? How long does it take to make the decision? How does the time differ between type of decision from your experience? When does it come to influence? When to re-visit?						Decision-maker speed
Do you make group decisions? With whom? When? How different/difficult?						Decision-makers deciding together

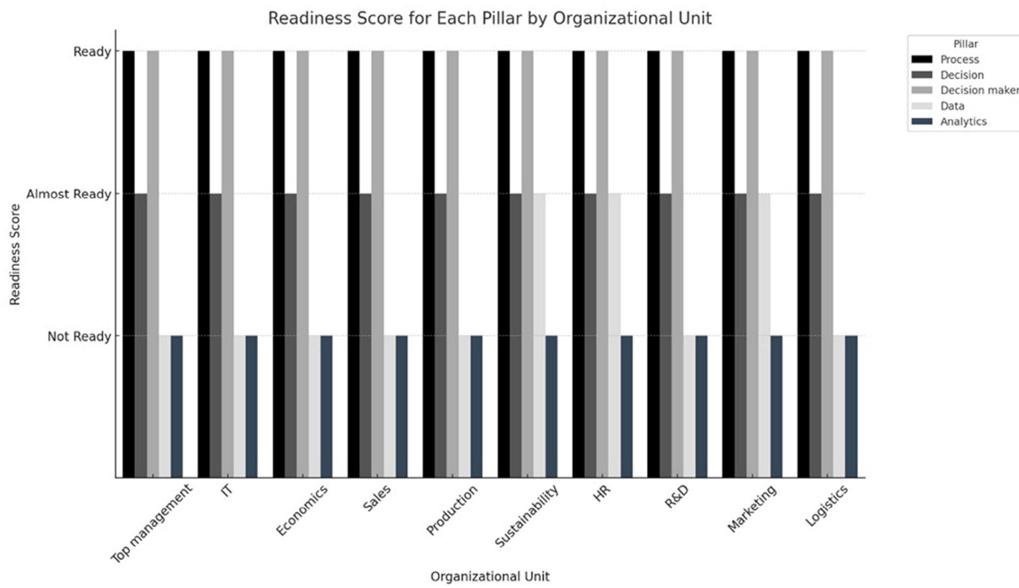

Fig. 3. DDDM readiness scores by organizational unit.

Table 2
Decision-making interviews schedule.

Monday	JAN 24th	14–15PM
Friday	JAN 28th	9–10AM
Monday	JAN 31st	11AM–12PM
Monday	JAN 31st	14–15PM
Monday	FEB 7th	11AM–12PM
Monday	FEB 7th	14–15PM
Monday	FEB 14th	11AM–12PM
Monday	FEB 14th	16–17PM
Wednesday	FEB 16th	14–15PM
Friday	FEB 18th	16–17PM

6. Other findings related to decision culture were identified during the interviews pertaining to: consensus-building in decision-making, openness and transparency, and most significantly that no one is afraid to make a wrong decision. This may be because data-driven top management support fosters an analytical decision-making culture [41,42] and is necessary for the digital transformation towards DDDM [43].

5.2. IT systems interview

Since we adopt a theoretical foundation which takes data and analytics as pillars of modern decision-making theory, the researchers have designed an IT system understanding questionnaire (See Appendix B). Interview responses revealed the below findings:

1. Most of the IT systems available are transactional or operational in nature e.g., MS NAV 2015 (ERP system); Pipechain (order management system); Centuri (document management system); GCT (customs and freight management); iPack (operational equipment efficiency); IDOS (maintenance planning for machines); ACENDO (invoice management systems-supplier invoices); AGDA PS (time reporting for HR); EDGE-HR (development interviews); and LIA (incident reporting system).
2. All transactional systems are off-the-shelf, rather than developed in-house. They are also hosted in-cloud, except for the ERP system.
3. The above list of transactional systems calls for both integration and decision systems. However, responses revealed a lack of such systems. The researchers believe that this is one of the key action points which needs to be considered. Correspondingly, heterogeneity of data sources without appropriate integration affects the link between the adoption of digital technologies and firm performance, and leads to a negative synergy with DDDM [12].
4. We, the researchers, have been informed during the IT systems interview that Power BI exists, but without dashboards, and that implementation is now taking place. We believe this is an important direction which will influence decision-making quality via making relevant dashboards available to decision-makers which they can rely on while making decisions. This adds to current research which emphasizes that comprehensive and integrated dashboards, with clear relationships and interconnectedness between the key metrics, are key to effective DDDM [44].
5. Responses revealed extensive use of Excel sheets. The researchers strongly believe this is an important enhancement point. Isolated Excel sheets lack governance and control. Perhaps the reason behind such use of Excel sheets is attributable to the lack of data warehouse, dashboards, and decision support environments. Accordingly, we think that progress with regard to those areas: dashboards, data warehousing, and decision support environment will address this issue adequately.
6. Responses revealed a lack of important data and analytics resources which the researchers strongly believe will hinder not only data-driven decisions, but the quality of decisions made at the company in general. Those resources which currently do not exist are:
   - Enterprise data warehouse
   - Big data management tools

Table 3
Decision-making interview' qualitative analysis.

Org. Unit	Five pillars analysis	Readiness level
Top management	– Decision: Clear decision scope (in/out). No decision accuracy model exists, but "*In the last couple of year, we have used after action review AAR as a model of evaluating projects and processes*". No error analysis mechanism used. Values influencing decisions are known "*innovation, wholehearted, action oriented*". – Decision-maker: Capability to make decisions, individually and in group (take longer). "*Big decisions, more than 50% are group decisions" & "On the other hand, we have very delegated responsibilities in the company to make decisions" & "The Chairman and the CEO take full responsibility of corporate decision, we do have shared management role of the company".* – Process: A clear process exists. "*When coming to the board we very often talk about 3 scenarios" & "The culture of the company is characterized by looking at different alternatives".* – Data: *The retail/food industry is so much data-driven. For big decisions e.g., SEK100M then we try to get hold of the data!* there exist lots of internal data, data market providers can supply the data if we pay for it. – Analytics: No use of analytics models. *No dashboards.* Yet, *willing to use models into decisions* and support collaborative decisions.	*Almost decision (evaluation!);* *Mature decision-maker;* *Mature process;* *Low data maturity (no clear ability to execute due to lacking tools);* *Low analytics maturity*
IT	– Decision: Clear decision scope (in/out). No decision accuracy model exists, but "*I usually think about time, cost, and quality".* No error analysis mechanism used. Values influencing decisions are known *e.g., sustainability.* – Decision-maker: Capability to make decisions on time, within a group or individually. Group decisions take longer time to make. – Process: Mixed processes exist, rather than one. – Data: Both *external* e.g., insights and recommendation from relevant research companies in the IT field (e.g., Gartner) and *internal* data are used, *after a Google search as a start.* – Analytics: No use of analytics models. *No dashboards*. No clear stance when it comes to the *willingness to use models into decisions.*	*Almost decision (evaluation!);* *Mature decision-maker;* *Mature process;* *Low data maturity, except for the latency and structure & lacking tools;* *Low analytics maturity*
Economics	– Decision: Clear decision scope (in/out). No decision accuracy model exists. No error analysis mechanism used. Values influencing decisions are known *e.g., "monetary, ecological and social".* – Decision-maker: Capability to make decisions on time, within a group or individually. Group decisions take longer time to make. – Process: A process exists, in different variations depending on the situation. – Data: The data used is mostly internal and there exist a *lack of external data* e.g., consumer behavior data. – Analytics: No use of analytics models. *No dashboards*. Yet, *willing to use models into decisions* and support collaborative decisions.	*Almost decision (evaluation!);* *Mature decision-maker;* *Mature process;* *Low data maturity, especially external;* *Low analytics maturity*
Sales	– Decision: Clear decision scope (in/out). No decision accuracy model exists. No error analysis mechanism used, "*We are bad in evaluating our historical decisions".* Values influencing decisions are known "*Owners want to be part of solving global environmental questions and to have happy employees".* – Decision-maker: Capability to make decisions on time, within a group or individually. Accountability at top management level. Group decisions take longer time to make. *"The company culture avoids putting anyone in the guilt feeling".* – Process: A clear process exists. *"I use different processes at different occasions".* – Data: There is a *lack of some internal data* which were lost during a major internal incident and *lack of external data* about customers! – Analytics: No use of analytics models. *No dashboards*. Yet, *willing to use models into decisions* and support collaborative decisions.	*Almost decision (evaluation!);* *Mature decision-maker;* *Mature process;* *Low data maturity;* *Low analytics maturity*
Production	– Decision: Clear decision scope (in/out). No decision accuracy model exists, "*but time & cost are used as metrics".* No error analysis mechanism used. Values influencing decisions are known "*Human, product quality, deliveries, economical".* – Decision-maker: Capability to make decisions on time, within a group or individually. Accountability at top management level. Group decisions take longer time to make. *"It is ok and legal to make mistakes!"* – Process: A clear process exists. – Data: The data used is mostly internal and there exists a *lack of external data. Added, it can take long to get the data you want.* – Analytics: *No use of analytics models, but willingness to support coordinated decisions. Extensive use of Excel!*	*Almost decision (evaluation!);* *Mature decision-maker;* *Mature process;* *Low data maturity, especially external & latency;* *Low analytics maturity*

(*continued on next page*)

Table 3 (*continued*).

Org. Unit	Five pillars analysis	Readiness level
Sustainability	– Decision: Clear decision scope (in/out). No decision accuracy model exists, but *"The most important metric differs by the decision situation"*. No error analysis mechanism used. Values influencing decisions are known, *"Social and environmental, where environmental are deeply linked to social"*. – Decision-maker: Capability to make decisions on time, within a group or individually. Accountability at top management level: *"We think it is important to fix consequences rather than blame someone"*. Group decisions "corporate management team" take longer time to make but "*Group decision render support and buy-in"*. – Process: A clear iterative process exists. "*Data collection and analysis are easy, in the sense that I enjoy them"* & *"Making the decisions is more challenging, because it is a group exercise"*. – Data: There is no lack of data problem, but *the data is not structured enough, and it can take a long time to collect.* – Analytics: No use of analytics models. Yet, *willing to use models into decisions* and "*use machines to help us humans make better decisions*".	*Almost decision;* *Mature decision-maker;* *Mature process;* *Almost data maturity, except for the latency and structure;* *Low analytics maturity*
HR	– Decision: Clear decision scope (in/out). No decision accuracy model exists. No error analysis mechanism used. Values influencing decisions are known. – Decision-maker: Capability to make decisions on time, within a group or individually. Accountability at top management level. Group decisions take longer time to make. *"We are sort of "kind" company i.e., we do not name and shame individuals for making wrong decisions"*. – Process: Different versions of the process exist. *"Do not want AI to take care of the whole process, we need to meet the person in question"*. – Data: *There exist a use of internal data* e.g., salary, personnel, attendance, and occupational injuries data. But, *no clear use of external data (may be ok for HR). but symptoms of data integration problem exist.* – Analytics: No use of analytics models. Single use of *dashboards e.g., employee well-being*. Yet, *willing to use models into decisions* is conditional to its rational and expected results.	*Almost decision;* *Mature decision-maker;* *Mature process;* *Almost data maturity, except for integration;* *Low analytics maturity*
R & D	– Decision: Clear decision scope (in/out). No decision accuracy model exists, but "*We aim to mix heart and mind at our company! It makes it hard for us since there is no right and wrong in the heart"*. No error analysis mechanism used, but *"We work with a model called After Action Review at which we set a purpose and goal and look at what we did right and wrong"*. Values influencing decisions are known e.g., *"Sustainability, wellness of employees, costs"*. – Decision-maker: Capability to make decisions on time, within a group or individually. Accountability at top management level. Group decisions take longer time to make. – Process: A clear iterative process exists. "*Sometimes it is hard for us to see the data while we are going through the decision making process!"*. – Data: *Mostly data comes from inside and minority from outside the company*. *We do not have all data always. Some data were lost in* a major internal incident. – Analytics: *No use of analytics models, but willingness to support coordinated decisions. Extensive use of Excel!*	*Almost decision;* *Mature decision-maker;* *Mature process;* *Low data maturity, especially external;* *Low analytics maturity*
Marketing	– Decision: Clear decision scope (in/out). No decision accuracy model exists. No error analysis mechanism used. Values influencing decisions are known *"Sustainability is important, but often contradict costs"*. – Decision-maker: Capability to make decisions on time, within a group or individually. Accountability at top management level. Group decisions take longer time to make. *"We are more of a "consensus" company, rather than "structure"" & "We are not afraid of making wrong decisions" & "We are pretty transparent in our company"*. – Process: A clear process exists, which is iterative. Well-understanding to the decision choices. – Data: *There exist a use of both internal* e.g., marketing & sales *and external data* e.g., data about competitors & target groups. – Analytics: No traceable use of analytics models, but rather purchase of analyzed data. *No dashboards*. Extensive use of Excel sheets! Yet, *willing to use models into decisions* and support collaborative decisions.	*Almost decision;* *Mature decision-maker;* *Mature process;* *Almost data maturity (internal tools are missing!);* *Low analytics maturity*

(*continued on next page*)

Table 3 (*continued*).

Org. Unit	Five pillars analysis	Readiness level
Logistics	– Decision: Clear decision scope (in/out). No decision accuracy model exists, but *"It is easier to know if you have made the wrong decision, compared to knowing that you have made the right decision!"*. No error analysis mechanism used. Values influencing decisions are known e.g., "*Cost-efficiency & sustainability"*. – Decision-maker: Capability to make decisions on time, within a group or individually. *"In our company, I am not afraid of making decisions"*. Accountability at top management level. Group decisions take longer time to make. – Process: A clear process exists, which is not iterative. Well-understanding to the decision choices. – Data: The data used is mostly internal e.g., production & sales and there exists a *lack of external data* e.g., consumer behavior data. Additionally, we only know what happened in the stores only weekly! – Analytics: There is a *lightweight use of planning model in SCM* e.g., customer demand forecast. But *no use of ML models*. No use even of BI i.e., *no dashboards*. Extensive use of Excel sheets! Yet, *willing to use models into decisions* and support collaborative decisions.	*Almost decision;* *Mature decision-maker;* *Mature process;* *Low data maturity, especially external;* *Low analytics maturity*

- Data lake environment
- Data analytics algorithms

This finding supports current research which affirms that organizations should make full use of big data analytics tools to accelerate the transition from traditional to data-driven decision-making and better achieve decision effectiveness, efficiency, and quality. This requires strengthening the IT infrastructure through adopting and improving platform systems, advanced analysis tools, and large-capacity data storage tools [45], as well as big data management tools, and integration and decision systems as previously suggested in finding 3.

7. Finally, it is also revealed that currently there is a lack of key important roles such as: Data Engineer, Data Scientist, Business Intelligence Specialist, Chief Data Officer, Data Warehouse Designer/Administrator. The researchers would like to emphasize the need for such roles in modern organizations which aim for digitalization, to increase their capability to effectively deploy data, technology, and talent through organization-wide processes, roles, and structures [46].

6. Conclusion

Data-driven digital transformation is a complex, resource-intensive, and iterative process requiring broad organizational involvement, definition of roles, and various big data analytics and AI capabilities, as exemplified in leading organizations such as Siemens [47] and AUDI [48]. This paper examines the readiness of organizations for DDDM and proposes an assessment model supported by two designed questionnaires. The model was applied in a case study organization in the Swedish food manufacturing industry to investigate its readiness for DDDM. Eleven detailed interviews were conducted: ten with various functional decision-makers using the questionnaire about how organizations make decisions, and one with the IT Manager using the questionnaire about IT systems in organizations. The data collected from the interviews were then analyzed in relation to known decision theories and state-of-the-art in decision-making. Due to its novelty and comprehensiveness, the theoretical framework upon which the study is grounded is DECAS, a modern decision theory. DECAS relies on five pillars: the decision, decision-maker, decision process, data, and analytics and was used as a reference model against which to compare interview results.

The key results reveal the areas that call for action within the organization. While the case study organization shows readiness in the decision-making process and decision-maker aspects, it falls short in the data and analytics pillars, indicating a significant gap in these areas. Furthermore, we offer targeted recommendations for organizations to enhance their readiness, emphasizing the need for considering integration and decision systems, development of dashboards, increasing data and analytics resources, and defining key roles necessary for digitalization and DDDM. The research findings and instruments could be used by other organizations for the same purpose of assessment, which will help save time and money as well as help in identifying DDDM pillars and structures within the organization which are not ready.

Accordingly, the main contribution of this study is a DDDM readiness assessment model which provides a systematic approach to evaluate an organization's readiness across five key pillars. The model is accompanied by a data collection questionnaire for profiling the readiness level, which can be adopted by organizations to assess their DDDM readiness and determine relevant actions.

This research contributes to the knowledge base in DDDM by utilizing DECAS as a reference model and extending it to practice. Hence, it enriches the understanding of DDDM, emphasizing the importance of integration of modern advancements in big data and analytics with the traditional decision-making elements in organizations in the digital era. Contribution to practice includes providing the model and questionnaires as practical tools that can be adopted by various organizations to assess and enhance their DDDM readiness. Furthermore, the study provides clear guidelines for addressing readiness gaps and shifting toward DDDM.

We strongly believe that the above findings have the potential to shape understanding and influence the future steps toward the parts of digitalization pertaining to data-driven decisions. The research was limited to a single case organization where eleven interviews were conducted with eleven different respondents. Future research could be extended to other similar, or related, organizations with more respondents and in a longitudinal fashion. In conclusion, this research significantly advances the understanding of DDDM readiness, offering valuable theoretical insights and practical tools. It highlights the necessity for balanced development across all DDDM pillars, including the decision, decision-maker, decision process, data, and analytics, for effective organizational digital transformation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Decision-maker questionnaire

Respondent . . .

Date/Time:

Decision Makers Interview Scenario

Interview objective
The objective of this interview is to understand the decision-making process at *Food Co.*

In the beginning of the interview, the researcher from LTU will explain background:

Background
— The classical decision theory is characterized by 3 elements: DECISION; DECISION PROCESS; DECISION MAKER
— Modern decision theory is characterized by 5 elements, the added 2 are: DATA & ANALYTICS
— Management = Decision Making
— It is the process of choosing among alternative courses of action and choose the option that achieves a certain goal or maximizes utility
— Bounded rationality decision makers may be rational but are limited in cognitive processing ability when confronted with complex problems
— *Satisficing* that even if the optimal decision is sought, bounded rationality and limited information may result in accepting a solution that is —good enough

Types of decisions
— Structured e.g., ROP
— Semi-structured e.g., Site Location & Production Scheduling
— Unstructured e.g., Vision

Decision-making process
— *Simon*:
—3 stages: a. intelligence *[takes large time]*; b. design *[larger]*; & c. choice *[fraction]!*
—*Brim*:
—5 stages: a. identify the problem; b. obtain information; c. produce possible solutions; d. evaluation solutions; & e. select best solution [later, a 6th phase of implementation was added]
—*Mintzberg*:
—3 phases: 1. Identification [decision recognition & diagnosis]; 2. Development [search & design], & 3. Selection [screen, evaluate, & authorization]
—Three schematic models:
—*Sequential* - e.g., Simon Model!
—*Anarchical* – e.g., *Garbage Can Model!*
—*Iterative* - e.g., Mintzberg Model!

Decision-making Styles
— *Solo human*
— Solo machine
— Coordinated i.e., human & machine

Interview Questions:

Question	*Respondent*
[1.] How many decisions do you usually take a(n) hour/day/week/month?	
[2.] What do you make decisions about? Which decisions do you make on an hourly, daily, weekly etc. basis?	
[3.] Who makes the decisions? Is it a single person? Or hierarchy where one approves the others? Are there levels or is the decision being made at a single level? Are they planned or unplanned? Is there a decision-making structure?	
[4.] Is there any decision that you would like to be able to do, but cannot? What is the reason for that? How do you handle that situation?	
[5.] Who bears the consequences of making wrong decisions? The question is about accountability	
[6.] What is the nature of decisions choices you make? That is, do you normally choose among binary options to make a decision? Or Continuous? Or else?	
[7.] Which process to make the decisions?	
[8.] Is there any part of the decision process that you experience especially hard or easy?	
[9.] What is the description of TIME as an important decision-making aspect? How long does it take to make the decision? How does the time differ between type of decision from your experience? When does it come to influence? When to re-visit?	
[10.] What data do you use to make your decisions? Or is it completely based on gut feeling? Do you lack any data to support your decisions?	
[11.] *which data should the decision maker analyze in a certain decision situation? How to decide on relevance of data for a certain decision? Is there a certain data quantity to use in association with a particular data-driven decision?*	

Question	Respondent
[12.] How do you know what the correct decision is? Who decides on correctness? Which metrics to use to describe a decision as correct or incorrect? What to do if metrics are contradicting? Whom to consult on evaluating decision correctness?	
[13.] Do you have an accuracy model for your historical decisions? The percent of FP & FN?	
[14.] Do you analyze errors? How does the analysis feedback the next decisions?	
[15.] Do you use data augmentation techniques e.g., rotate, blur, scale, etc. at all? If yes, why/how/when?	
[16.] Do you use models to support the decision-making process? Which model types?	
[17.] What VALUES to cater for the most in order to evaluate your decisions? Is it monetary e.g., cost/benefit analysis? Or social e.g., saving peoples' lives? What happens if there is contradiction between values?	
[18.] Do you make group decisions? With whom? When? How different/difficult?	
[19.] What is your stance with regards to solo-human, solo-machine, and coordinated decisions?	
[20.] Are you willing to rely on data and analytics in making decisions? When? When not?	
[21.] What enabler do you need to rely on data and analytics in making decisions? What challenges currently exist: personal and organizational?	
[22.] Which IT systems do you currently use? How frequent? For which purpose? Do they provide you with dashboards? How much do you rely on them when making decisions?	
[23.] Anything else you think is relevant to decision-making and you would like to add?	
[24.] Is there any question you think that we might have missed to ask in general?	

Appendix B. IT systems questionnaire

Interview Questions:

Question	Respondent
[1.] Which system types do you currently have operational/transactional; decisional; integration; communication/collaboration; functional; others	
[2.] Operational/transactional systems	
[3.] Decisional systems	
[4.] Integration systems	
[5.] Communication/collaboration systems	
[6.] Functional systems	
[7.] Other systems	
[8.] Which ones are home-grown? i.e., developed in -house	
[9.] Which ones are off-the-shelf?	
[10.] Which ones are on-prem?	
[11.] Which ones are on-cloud?	
[12.] How do you manage master data? i.e., MDM	
[13.] How do you manage big data?	
[14.] How do you manage analytics and algorithms?	
[15.] Do you have an enterprise data warehouse? Or data marts?	
[16.] Which dashboard tools or platform to use? Its scope?	
[17.] Do you have an analytics sandbox? Explain its scope and functionality, users, etc.	
[18.] Do you have a data lake?	
[19.] Explain corporate data in terms of structure, semi-structured and unstructured? Explain in terms of their percentage, pre-processing, utilization, and related other issues	
[20.] Explain the team roles related to operational versus decisional systems	
[21.] Explain big data analytics team skills/competencies?	
[22.] Which of these titles do you currently have within the team: data engineer? Data scientist? Business Intelligence Specialist? Chief Data Office? Data Warehouse Designer/administrator?	
[23.] Explain the role of data in decision making at the enterprise	
[24.] Explain the influence of new technology e.g., big data, AI, ML, IoT, etc. on your last 3-5 IT projects?	
[25.] Other related relevant points?	
[26.] Other questions that you think are relevant?	

Appendix C. Readiness levels

See Fig. 4.

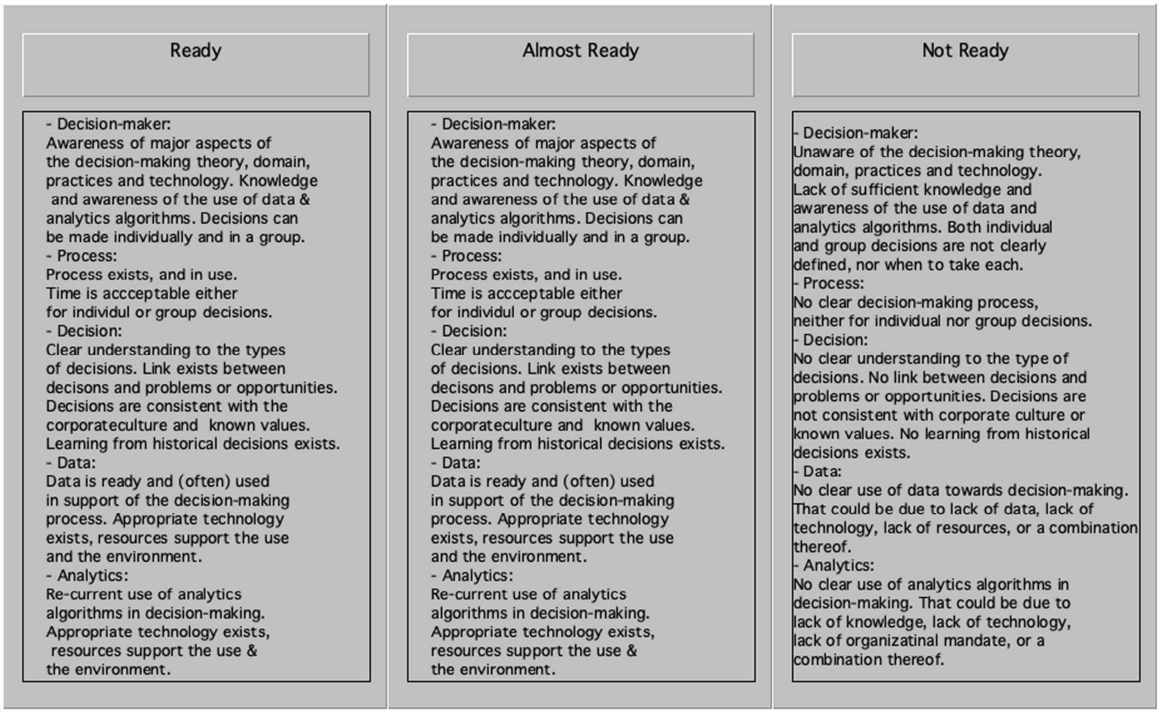

Fig. 4. Readiness levels.

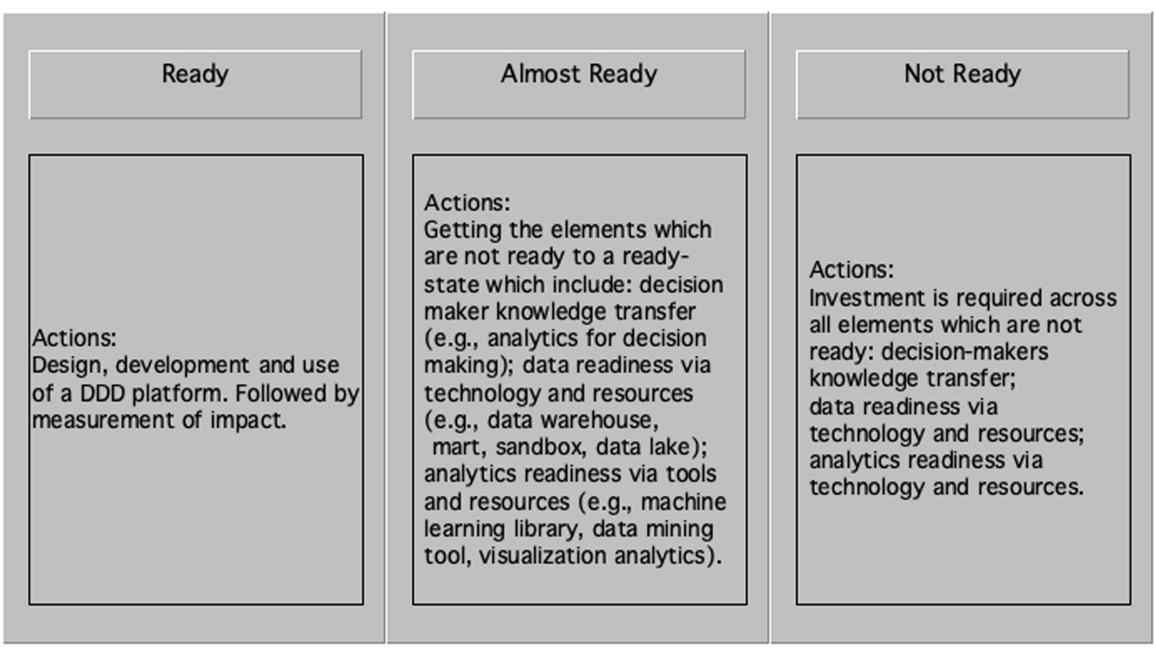

Fig. 5. Actions.

Appendix D. Actions

See Fig. 5.

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