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A Matrix for Assessing Data-Driven Culture in Teams

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Abstract

Establishing a data-driven culture in teams is on the agenda for many managers and analytics leaders. With a data-driven culture in place, it is envisioned that investments in analytics can be used to their full potential. In practice, most organizations struggle to establish a data-driven culture in teams and have few tools available to assess the level of maturity.

Related research has focused on maturity models in business intelligence & analytics that target the organizational level. Hence, these maturity models provide limited support for assessing the team level, e.g., why some teams do not develop a data-driven culture.

This paper used a systematic literature review and an online questionnaire to develop a matrix for assessing a team's maturity in data-driven culture. The matrix synthesizes previous work in analytics and group development. Findings from the literature review revealed a mismatch between problems addressed by the research community and perceived problems in practice by organizations.

Keywords

Data-driven culture, data-driven organizations, analytics, business intelligence, maturity models, group development.

Introduction

Frequently using analytics to gain competitive advantages and deriving new insights are now mainstream in successful organizations. Organizations that have invested heavily in analytics technology over the last decade are now getting returns on their investments (Brynjolfsson et al. 2021; NewVantagePartners 2022). Similarly, academic research has reported positive effects of establishing a data-driven culture for different domains, e.g., strategic decision-making and organizational performance (Cao and Duan 2015), product innovation and process innovation (Chatterjee et al. 2021), customer development and firm performance (Agyei-Owusu et al. 2021), and cloud computing security (Wang et al. 2020).

According to Boyd (2012, analytics can be described as "*the scientific process of transforming data into insight for making better decisions*", and it is commonly categorized into (Delen and Ram 2018; Watson 2013): descriptive analytics, predictive analytics, and prescriptive analytics. When analytics is frequently used within an organization for decision-making, a data-driven culture is said to emerge. According to Kiron et al. (2012, a data-driven culture can be defined as "*A pattern of behaviors and practices by a group of people who share a belief that having, understanding and using certain kinds of data and information plays a critical role in the success of their organization.*".

Although the road to success seems to be frequently using analytics and establishing a data-driven culture, the problem is that most organizations struggle to establish a data-driven culture. For example, NewVantagePartners (2022 reported in their 2022 survey that only 19,3% of the Fortune 1000 organizations had established a data-driven culture, and the numbers have been steadily declining each year from 28,3% in 2019. In the same survey, 91,9% of the respondents (executives) claimed that cultural factors were the most common barrier to becoming data-driven. At the same time, 92,1% of the respondents claimed that they are getting returns on their data and AI investments, which indicates a high analytics maturity.

Few large organizations are truly data-driven in all parts of the organization, e.g., they can be mature in advanced analytics in some business areas, and in others, decisions are mostly based on gut feeling. In practice, it means that organizations do not use their analytics investments to their full potential.

An organization's maturity in business intelligence & analytics can be assessed by a maturity model, e.g., TDWI's BI maturity model (Eckerson 2009), analytics maturity model (LaValle et al. 2011). The limitation of these maturity models is that they tend to target the overall organization and have limited support for capturing cultural factors. Hence, an organization that is aware that cultural factors are the most common barrier and intends to assess a team's maturity in data-driven culture will get limited help from a maturity model in business intelligence & analytics.

Furthermore, we have observed teams that are skilled in analytics but have poor group development, i.e., collaboration within the team is poor. The practical consequences are that team members do not openly share their data and findings, which in turn becomes a barrier to using analytics to its full potential in the team. In this situation, the team needs to improve its collaboration using, e.g., the Integrated Model of Group Development (Wheelan 2016).

The objective of this paper is to investigate *how maturity in data-driven culture can be assessed in a team*, given the limitations of existing maturity models and problems related to poor group development.

In the remainder of this paper, we present a brief background to business intelligence & analytics, maturity models in business intelligence & analytics, and the Integrated Model of Group Development. Thereafter, we present our research approach. In the succeeding sections, we present our findings. Finally, related work and conclusions are presented.

Background

In this section, we provide a brief introduction to business intelligence & analytics, maturity models in business intelligence & analytics, and the Integrated Model of Group Development.

Business Intelligence & Analytics

The aim of business intelligence & analytics is to analyze collected data to make better decisions and is commonly divided into (Delen and Ram 2018; Watson 2013): i) descriptive analytics, ii) predictive analytics, and iii) prescriptive analytics. Descriptive analytics investigates the past, e.g., with the aid of a data warehouse. Predictive analytics investigates the near future, e.g., with the aid of data mining. Finally, prescriptive analytics gives decision recommendations or automatically makes decisions, e.g., with the aid of a rule system. Predictive analytics and prescriptive analytics are also grouped together as advanced analytics.

In the literature, there are well-known success stories from organizations that have successfully applied business intelligence & analytics, e.g., Harrah's (Wixom and Watson 2010) and Continental Airlines (Anderson-Lehman et al. 2008). On a more broader scale, McAfee and Brynjolfsson (2012 investigated 330 companies and concluded that "*[t]he more companies characterized themselves as data-driven, the better they performed on objective measures of financial and operational result. In particular, companies in the top third of their industry in the use of data-driven decision making were, on average, 5% more productive and 6% more profitable than their competitors*". In a follow-up study by Brynjolfsson et al. (2021, 30 000 manufacturing firms and their usage of predictive analytics was investigated. Their findings were that manufacturing firms that used predictive analytics had significantly higher productivity than their competitors.

Data-driven culture and data-driven organizations are frequently used interchangeably. However, there is a subtle difference. Data-driven culture is more used to describe the usage of analytics among people, whereas data-driven organization is more used to describe the usage of analytics from an overall organizational perspective.

Maturity Models in Business Intelligence & Analytics

The purpose of maturity models in business intelligence & analytics is to assess the strengths and weaknesses of an organization's business intelligence & analytics usage. Typically, a maturity model is divided into levels (or stages), dimensions, and criteria. Below in Figure 1 is a subset of the maturity model by LaValle et al. (2010. The maturity model was developed based on an international survey of 3000+ executives, managers, and analysts.

	Aspirational	Experienced	Transformed
Data management	• Limited ability to capture, aggregate, analyze or share information and insights.	• Moderate ability to capture, aggregate and analyze data. • Limited ability to share information and insights.	• Strong ability to capture, aggregate and analyze data. • Effective at sharing information and insights.
Analytics in action	• Rarely use rigorous approaches to make decisions. • Limited use of insights to guide future strategies or guide day-to-day operations	• Some use of rigorous approaches to make decisions • Growing use of insights to guide future strategies, but still limited use of insights to guide day-to-day operations.	• Most use rigorous approaches to make decisions • Almost all use insights to guide future strategies, and most use insights to guide day-to-day operations.

Figure 1 A subset of the maturity model developed by LaValle et al. (2010

Maturity models in business intelligence & analytics can be categorized into general maturity models (LaValle et al. 2010), or domain-specific, e.g., Higher Education (Elsa and Xiaomeng 2022), Healthcare (Brooks et al. 2013).

Maturity models are widely used in business as a conceptual tool to assess an organization's capabilities. However, critiques have been raised against maturity models since they tend to lack a theoretical foundation and description of how they were developed (Lahrmann et al. 2011).

Integrated Model of Group Development

The Integrated Model of Group Development was developed by Wheelan (2016 and integrates earlier suggested group development models, e.g., (Tuckman 1965), into four group development stages:

- **Dependency & Inclusion**. In the first stage, group members try to establish their membership and safety in the group. When a group is initiated, several factors are likely to be unclear, such as purpose, roles, or future activities. Consequently, most group members will assume that the leader of the group will make decisions and show the way forward. At this stage, there is little conflict, and the group leader is rarely challenged.
- **Counter-Dependency and Fight**. In the second stage, group members start to challenge the group leader regarding factors such as purpose, roles, or future activities. The conflicts and debates in the second stage are needed to establish a shared understanding of purpose, values, norms, and structure.
- **Trust and Structure**. In the third stage, group members have established trust and structure in the group, which implies more open and task-oriented communication. The group leader becomes more consultative and less directive. Furthermore, the group has a much clearer understanding of shared goals.

- **Work and Productivity**. In the fourth stage, the group members focus on completing the tasks with high quality. Task-related discussions are encouraged as input to decision-making. Furthermore, the group is perceived by others as a high-performance team.

The Integrated Model of Group Development is complemented by a Group Development Questionnaire (GDQ) (Wheelan 2016) that allows groups to assess group development maturity and take responsive actions.

According to Åkerlund et al. (2021, the Integrated Model of Group Development has been the foundation in about 30 doctoral theses, 60 peer-reviewed articles, and is widely used by certified GDQ consultants around the world. Hence the model is well used within research and practice for assessing group development.

Research Approach

In this section, we present the research approach taken to address how a team's maturity in data-driven culture can be assessed.

To assess how maturity in data-driven culture can be assessed in a team, we decided to use definitions of what a data-driven culture means as a starting point for our investigation. Definitions are useful as they offer guidance on the characteristics of a data-driven team. As there are many suggested definitions of data-driven culture, we used a systematic literature review to discover suggested definitions.

The findings from the systematic literature review guided our development of a matrix for assessing a team's maturity in data-driven culture.

We used an online questionnaire to validate some of the findings from the literature review and elements of the matrix. Our target group with the questionnaire was BI & Analytics consultants working on a daily basis with clients that intend to become data-driven and are familiar with the concept of a data-driven culture.

Systematic Literature Review

The systematic literature review follows the guidelines in (Fisch and Block 2018; Kitchenham et al. 2009):

- **Research question (for the review)**: what is meant by a data-driven culture?
- **Search string**. The search string "*data-driven culture*" was used within title or abstract. An assumption was made that if data-driven culture is mentioned in the title or the abstract, there is a high chance that the article has a definition of data-driven culture. Initial testing was done with more general search strings, e.g., "data-driven AND culture". As the general search strings generated a too-big search result, e.g., 100 results vs 7000 in one database, it was decided to prune the search results using a more specific search string.
- **Identify data sources**. Searches were done in nine data sources: ACM, EBSCO, Emerald, IEEE, SAGE journals, Science direct, Scopus, Taylor & Francis, and Web of Science.
- **Inclusion and exclusion criteria**. Potential articles were included if they meet the following criteria: i) articles written in English, ii) published 2012-2021 (last ten years), iii) published in journals, conferences, or workshops, and iv) data-driven culture is mentioned in the title or the abstract. Potential articles were excluded if they matched any of the following criteria: i) editorials, ii) articles with no references, or iii) duplicates.

An overview of the search procedure is presented in Figure 2.

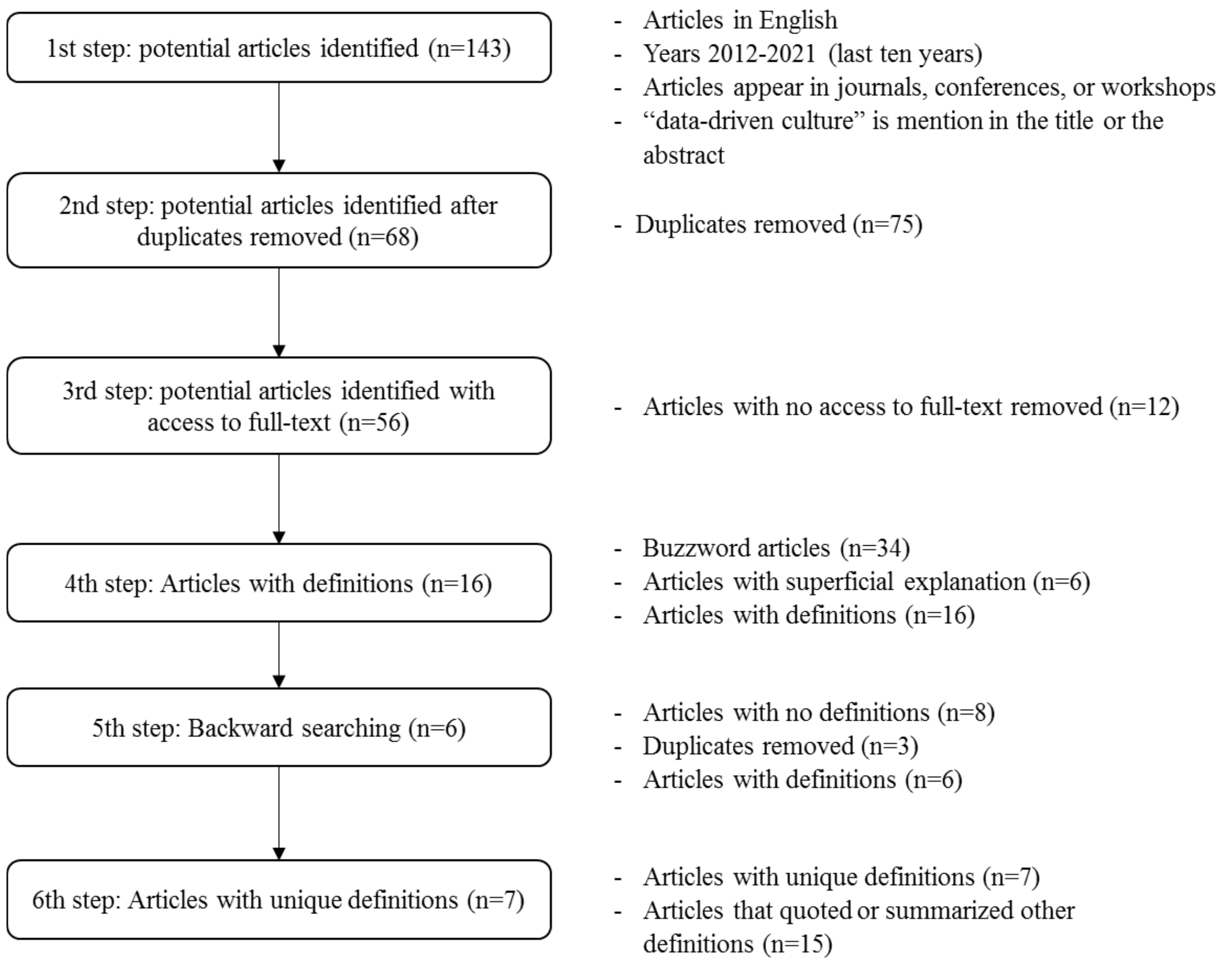

Figure 2 Overview of search procedure

In the 1st step 143 potential articles matched the inclusion criteria. After removing duplicates in the 2nd step and filtering out articles with no full-text access, 56 potential articles remained. Each of the 56 articles was categorized in how they described a data-driven culture. Most of the articles used data-driven culture in a superficial manner and did not explain the term. A handful of articles had superficial explanations such as “decisions are based on data”. Out of 56 potential articles, 16 articles provided definitions of a data-driven culture. A backward search was done from the 16 articles that provided definitions, i.e., what references were cited when defining data-driven culture. The backward search generated 6 new articles with definitions. These new articles were 3 articles from the management literature (e.g., Harvard Business Review, MIT Sloan Review) and 3 academic articles that had not used data-driven culture in the title or abstract. Thus, the total number of articles with definitions was 22. Out of the 22 articles, 7 articles provided unique definitions and 15 articles quoted or summarized other definitions.

Online questionnaire

We used an online questionnaire to collect data from BI & Analytics consultants at a large consultancy company in Sweden, Norway, Denmark and Finland. Each respondent was informed about the purpose of the data collection and that answers were anonymous. The data collection was done between April 28 2022 and May 15 2022, and 31 valid answers were received.

Findings from Systematic Literature Review

In this section, we present the findings from the systematic literature review.

Publications

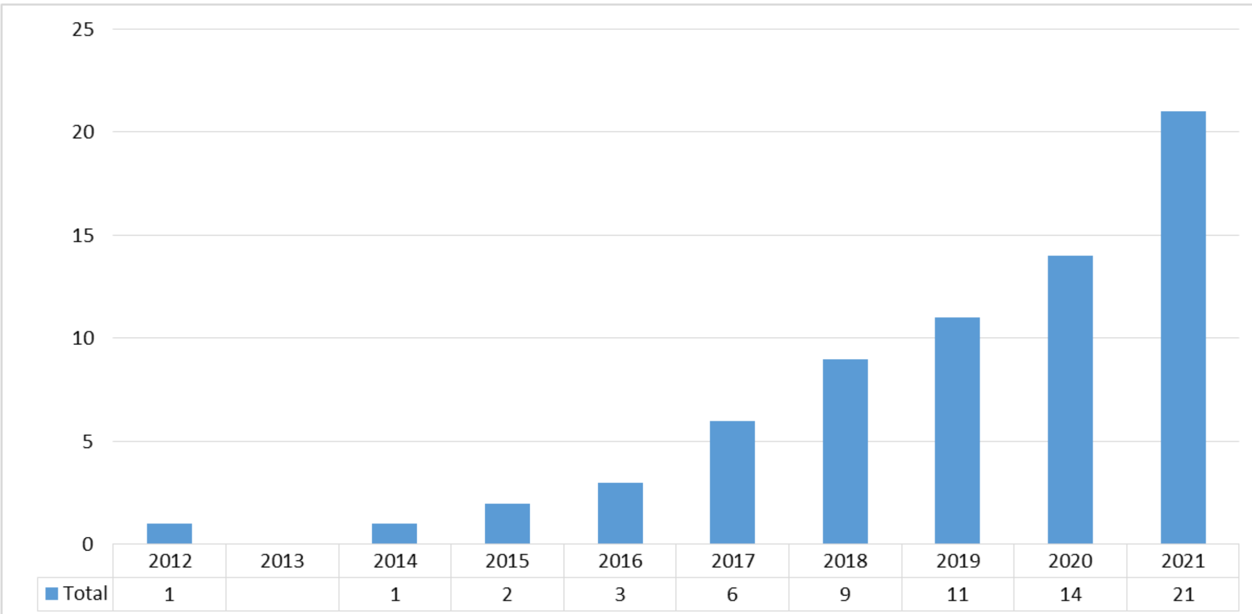

Figure 3 Potential articles identified (n=68) after duplicates removed.

As seen in Figure 3, research articles that mention data-driven culture in the title or abstract has steadily increased for 2012-2021. Most articles during this period are published at conferences in information systems, Figure 4.

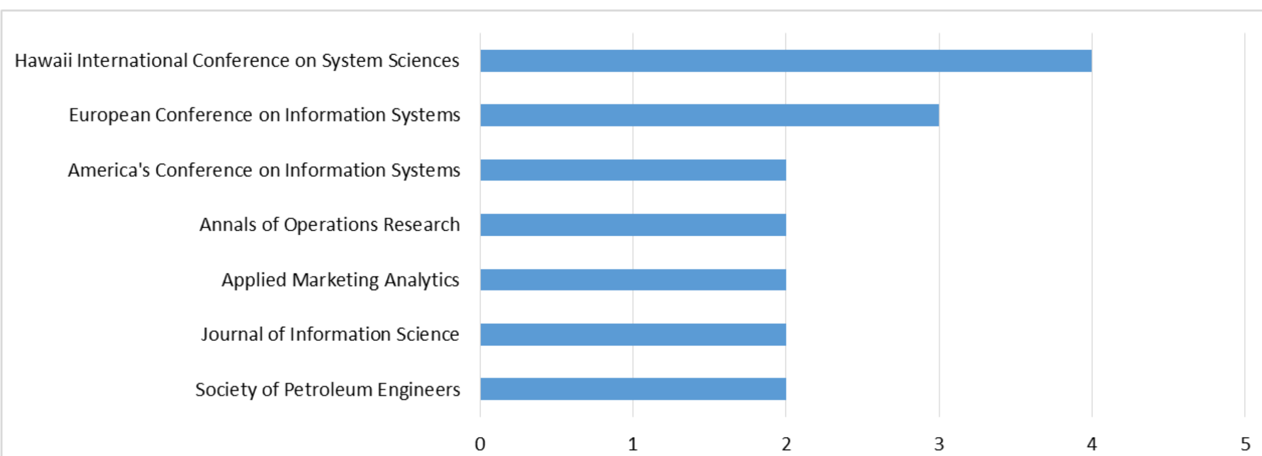

Figure 4 Top publication forums (more than one article) for 2012-2021.

Definitions, Topics, and Research Approaches

In total, 22 articles with definitions were identified, of which 19 were academic research articles. As seen in Table 1, the 19 research articles mainly investigated relationships between business analytics, data-driven culture, and a chosen application area. Structural equation modelling dominates as the chosen method for analyzing collected data.

Table 1 Overview of research articles (n=19) with definitions

Source	Topic	Research approach
Cao and Duan (2014	Relationship between business analytics, data-driven culture, information processing capabilities, and competitive advantage.	Partial least squares structural equation modelling.
Holsapple et al. (2014	Ontology for business analytics.	Literature review.
Duan and Cao (2015	Relationship between business analytics, data-driven culture, and innovation.	Partial least squares structural equation modeling.
Cao and Duan (2015	Relationship between business analytics, data-driven culture, decision-making affordances, strategic decision-making, and organizational performance	Partial least squares structural equation modelling.
Gupta and George (2016	Relationship between big data analytics capability and firm performance.	Resource-based theory, higher-order formative construct.
Wang et al. (2019	Relationship between big data analytics, organizational performance.	Online survey, configuration theory and fuzzy-set qualitative comparative analysis.
Wang et al. (2020	Relationship between business analytics, data-driven culture, and cloud computing security.	Partial least squares structural equation modelling.
Herden (2020	Relationship between competitive advantage, and analytics.	Case study.
Zhang et al. (2020	Relationship between big data analytical intelligence and customer relationship management performance.	Partial least square analysis, regression analysis.
Duan et al. (2020	Relationship between business analytics and innovation	Partial least squares structural equation modeling.
Chaudhuri et al. (2021	Relationship between data-driven culture, process performance, product innovation, and organizational performance.	Partial least squares structural equation modeling.
ZareRavasan (2021	Relationship between big data analytics, and innovation performance.	Partial least squares.
Chatterjee et al. (2021	Relationship between data-driven culture, product innovation, and process innovation.	Least squares structural equation modelling.
Yu et al. (2021a	Relationship between data-driven culture, digital technology orientation, big data analytics capability, and operational performance	Structural equation modeling and ordinary least square regression.
Campbell et al. (2021	Relationship between analytical capabilities and organizational performance.	Structural equation modeling.
Yu et al. (2021b	Relationship between big data analytics capability, supply chain finance integration, and data-driven culture.	Structural equation modeling.

Gurusinghe et al. (2021	Relationship between predictive HR analytics, talent management, and data-driven culture.	Technology-Organisation-Environment (TOE) framework, Resource-Based View (RBV) theory.
Agyei-Owusu et al. (2021	Relationship between data-driven culture, customer development, and firm performance.	Partial least squares structural equation modelling.
Medeiros and Maçada (2021[1]	Relationship between data-driven culture, business analytics, and competitive advantage.	Structural equation modelling.

Three out of the 22 articles with definitions came from the management literature (Kiron et al. 2013; Kiron and Shockley 2011; Kiron et al. 2012).

Most of the 22 articles either quoted or slightly rephrased the definitions of (Kiron et al. 2013; Kiron and Shockley 2011; Kiron et al. 2012) or (Gupta and George 2016). However, seven articles provided unique definitions of data-driven culture, see Table 2.

Table 2 Unique definitions of data-driven culture

Source	Definition
Kiron and Shockley (2011	A data-oriented culture is a pattern of behaviors and practices by a group of people (in a department, line of business or enterprise) who share a belief that having, understanding and using certain kinds of data play a critical role in the success of their business.
Kiron et al. (2012	A pattern of behaviors and practices by a group of people who share a belief that having, understanding and using certain kinds of data and information plays a critical role in the success of their organization.
Gupta and George (2016	.. the extent to which organizational members (including top-level executives, middle managers, and lower-level employees) make decisions based on the insights extracted from data.
Herden (2020	A data-driven culture is described as a common organization-wide culture that supports, promotes, and embeds shared Analytics-driven ways of thinking, decision making, and acting and accepts data and information as critical for success.
Zhang et al. (2020	Data-driven culture refers to the beliefs, attitudes, and opinions regarding data-driven decision making in management practices and operational processes.
ZareRavasan (2021	Data-driven culture refers to the degree that senior-level executives are committed to [Big Data Analytics] BDA and how they make decisions that stem from intelligence.
Medeiros and Maçada (2021	The [Data-driven culture] DDC refers to organizational norms, values and behavioral patterns, resulting in systematic ways to create, gather, consolidate, analyze the data and make it available to the right public, which includes the extension of the use of these data for making from business decisions and management support to analysis, receptivity to learn and disseminate knowledge, as well as an inclination to change and improve ways of working and making data-driven decisions.

[1] Published online May 2021 by the publisher, appeared in print March 2022. In this data collection we include the article, since it has been available at the publisher already in May 2021.

A Matrix for Assessing a Team's Maturity

In this section, we present a matrix for assessing a team's maturity in data-driven culture.

According to Table 2, seven unique definitions of data-driven culture were discovered. Our takeaways from the definitions regarding characteristics are:

- **Frequency**. Both Gupta and George (2016 and ZareRavasan (2021 emphasize the frequency (extent/degree) of using data-driven decision making. Frequency can also be derived from definitions that emphasize “pattern of behaviors and practices” or that it is “common”. In order for something to be a pattern or to be categorized as common, the occurrence of data-driven decision making is frequent.
- **Data-driven decision making**. Most definitions explicitly mention data-driven decisions or that decisions are based on analyzed data.
- **Shared understanding**. Underpinning all definitions is an assumption that a group of people share the same understanding and commitment that data-driven decision making is essential for success.

By merging the characteristics from the definitions in Table 2 with a stronger emphasis on using the term *analytics* (as it includes deriving insights from data), a new definition can be developed:

> A data-driven culture is defined as a group of people that frequently use analytics to influence their decision-making in an open and trusting environment.

Underpinning the definition are two essential dimensions for a data-driven culture: i) maturity in analytics, and ii) how well a group of people can collaborate. Progression in analytics is often described as a ladder with descriptive analytics, predictive analytics, and prescriptive analytics. Similarly, how well a group of people can collaborate can be captured by group development models, e.g., (Wheelan 2016). By combining the two dimensions a simple matrix can be developed, Figure 5.

		Group development stages (Wheelan 2016)			
		Dependency & Inclusion	Counter-Dependency and Fight	Trust and Structure	Work and Productivity
Analytics progression (Watson 2013)	Prescriptive analytics				
	Predictive analytics				
	Descriptive analytics				
	No analytics				

Figure 5 A matrix for assessing a team's maturity in data-driven culture

The intersection of analytics maturity and group development can be categorized into three categories:

- **Territorial analytics (white area)**: This category represents teams that can apply all types of analytics, but are still in the early stages of group development. Members of such a group do not openly share information and trust each other. Hence the usage of analytics tends to be territorial, i.e., analytics is used to highlight only the positive aspects of your own responsibilities.
- **No analytics (grey area)**: This category represents teams that do not frequently use analytics, but still evolve as a group and become successful.

- **Data-driven culture (green area)**: This category represents teams that frequently apply all types of analytics, have established trust & structure, and are considered a high-performance team.

For example, a group that frequently uses analytics (descriptive, predictive, or prescriptive) and has a group development level of three or four in the group development model of Wheelan (2016 has established a data-driven culture. A group of people who frequently use analytics but do not trust each other enough to share information or findings, or frequently blame others has not established a data-driven culture.

		Group development stages (Wheelan 2016)			
		Dependency & Inclusion	Counter-Dependency and Fight	Trust and Structure	Work and Productivity
Analytics progression (Watson 2013)	Prescriptive analytics				
	Predictive analytics			Team 2	
	Descriptive analytics	Team 1			
	No analytics				

Team 1				
Analytics progression	No analytics	Descriptive analytics	Predictive analytics	Prescriptive analytics
Group development stages	Dependency & Inclusion	Counter-Dependency and Fight	Trust and Structure	Work and Productivity
Team 2				
Analytics progression	No analytics	Descriptive analytics	Predictive analytics	Prescriptive analytics
Group development stages	Dependency & Inclusion	Counter-Dependency and Fight	Trust and Structure	Work and Productivity

Figure 6 Matrix vs. rows in a maturity model

An alternative to developing a matrix would be to extend an existing maturity model in business intelligence & analytics and add rows for analytics progression and group development stages, Figure 6. In case multiple teams are assessed, the matrix has an advantage as it is easier to get a birds-eye view of the status of several teams.

Maturity models in business intelligence & analytics cover more dimensions than the suggested matrix; hence the matrix complements existing maturity models.

Findings from online Questionnaire

We distributed an online questionnaire to BI & Analytics consultants at a large consultancy company to validate some of the findings from the literature review and matrix elements. In particular, we wanted to validate four aspects:

- **Definitions**. The academic research frequently cites definitions by Kiron et al. (2013; Kiron and Shockley (2011; Kiron et al. (2012 or Gupta and George (2016, do the BI & Analytics consultants prefer these definitions as well, or are more superficial definitions preferred?
- **Skills in analytics**. What type of skills in analytics does a group of people need to become data-driven? This question is related to the analytics progression in Figure 5.
- **Importance of group development**. Underpinning the extracted definitions is an assumption that good group collaboration is essential for a data-driven culture, do the BI & Analytics consultants share this view? This question is related to the group development stages in Figure 5.
- **Example of territorial analytics**. The matrix presented in Figure 5 claims that a group that is very skilled in analytics and has poor group collaboration has not established a data-driven culture. This question is related to the intersection of analytics progression and group development stages in Figure 5.

Definitions

The BI & Analytics consultants were presented with a list of definitions (without the source) that included: i) the seven unique definitions in Table 2, ii) our new definition, and iii) two superficial definitions (Decision-making is based on data instead of intuition; Decisions are based on data). These two superficial definitions were discovered during the literature review. The consultants were asked to choose one definition (or provide a new one) that best described what is meant by a data-driven culture.

Table 3 Definitions preferred (more than two votes) by BI & Analytics consultants.

Definitions	Votes
The [Data-driven culture] DDC refers to organizational norms, values and behavioral patterns, resulting in systematic ways to create, gather, consolidate, analyze the data and make it available to the right public, which includes the extension of the use of these data for making from business decisions and management support to analysis, receptivity to learn and disseminate knowledge, as well as an inclination to change and improve ways of working and making data-driven decisions. - (Medeiros and Maçada 2021)	10
A data-driven culture is described as a common organization-wide culture that supports, promotes, and embeds shared Analytics-driven ways of thinking, decision making, and acting and accepts data and information as critical for success. - (Herden 2020)	8
.. the extent to which organizational members (including top-level executives, middle managers, and lower-level employees) make decisions based on the insights extracted from data. - (Gupta and George 2016)	4

As seen in Table 3, the BI & Analytics consultants preferred the definition by Medeiros and Maçada (2021, which was the most elaborative definition. The definition by Gupta and George (2016 is preferred by both BI & Analytics consultants and academic researchers. Superficial definitions were not favored, as they received only two votes in total. Finally, we conclude that our suggested new definition was not preferred by BI & Analytics consultants, not a single vote.

Skills in Analytics

We asked the BI & Analytics consultants, "*Assume that you intend to raise the competence and skills in a group that is not data-driven. What is important during the first year with respect to skills and competence?*".

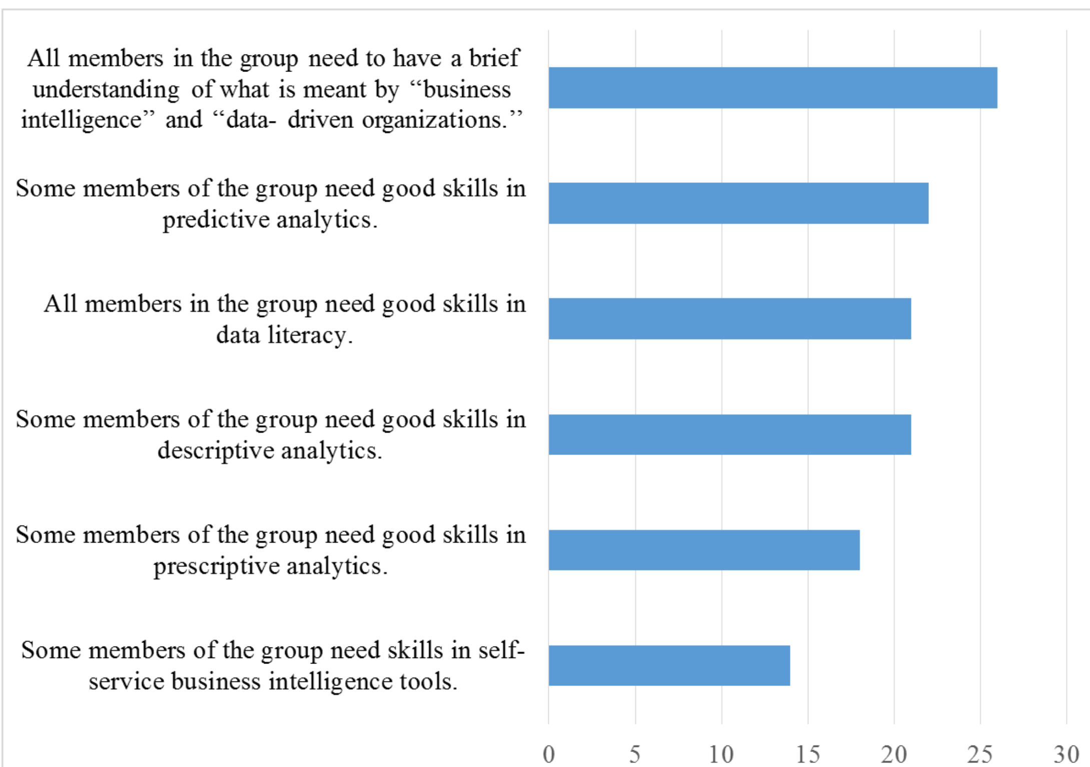

Figure 7 Important skills in analytics to raise during the first year (more than 10 votes).

According to the BI & Analytics consultants, it is important that all group members have a brief understanding of business intelligence & analytics, data-driven organizations, and good skills in data literacy. However, not all members need to have good skills in the different types of analytics or associated tools.

Importance of Group Development

We asked the BI & Analytics consultants, "*To what extent is group development, i. e., how well a group of people can collaborate, important for having a data-driven culture?*".

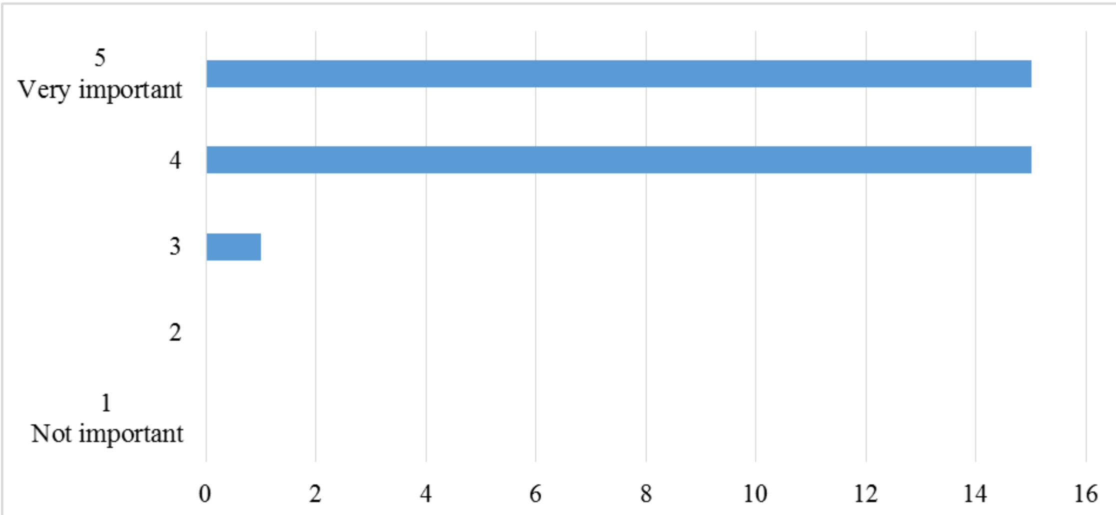

Figure 8 To what extent is group development important for having a data-driven culture?

Based on the answers presented in Figure 8, we conclude that BI & Analytics consultants believe that good group development is highly important for having a data-driven culture.

Example of Territorial Analytics

We asked the BI & Analytics consultants if "*.. a group of people who frequently use analytics, but do not trust each other enough to share information or findings, or frequently blame others.*" has established a data-driven culture?

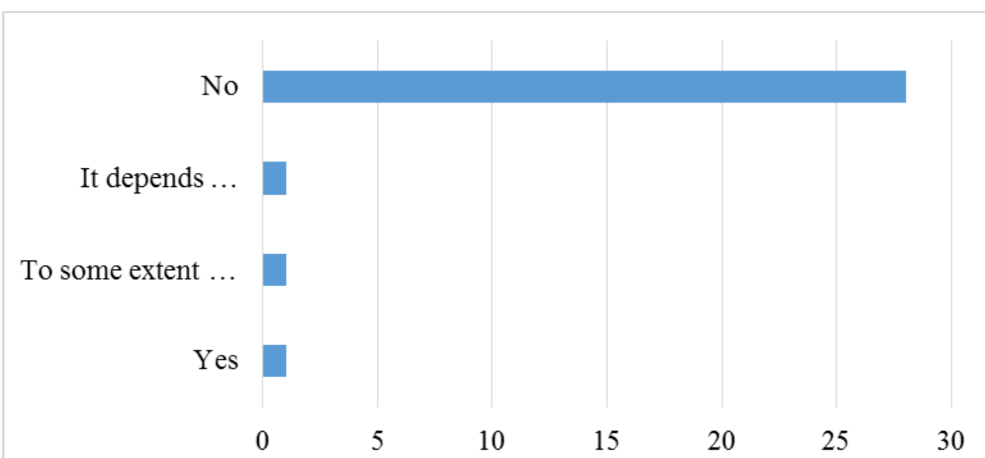

Figure 9 Has a group that frequently uses analytics, but does not trust each other enough to share information or findings, established a data-driven culture?

The majority (90%) of the BI & Analytics consultants argue that such a group has not established a data-driven culture, see Figure 9.

Discussion

Both the extracted definitions (Table 2) and the responses from the BI & Analytics consultants (Figure 8, Figure 9) indicate that good group development is a prerequisite for establishing a data-driven culture. Hence, a maturity model for data-driven culture (or organization) should assess analytical capabilities and group development.

Current literature on assessing data-driven culture at the group level is limited and fragmented. For example, a simple maturity model for data-driven organizations is presented in (Berndtsson et al. 2018). Although a dimension for *people* is present, it is mostly related to people's trust and feelings towards using analytics. None of the categories captures how well a group can collaborate when they are using analytics. A more complex maturity model is presented in (Buitelaar 2018) with 10 dimensions and 5 stages. Three of the dimensions (skill, leadership, culture) are related to people working in a group. The dimension *skill* focus on people's skills in analytics, data literacy, etc. The leadership dimension and the culture dimension are mostly related to increasing the analytical maturity, getting analytics on the agenda, and spreading usage of analytics. None of the dimensions capture skills in group development. The analytics maturity model of LaValle et al. (2011 is one of the most frequently cited maturity models for analytics adoption with six dimensions and three stages. Group development is present (fragmented) in two dimensions: key obstacles, and data management. A key obstacle at the first stage *Aspirational* is that the organization has a culture that does not encourage sharing information. In the third stage *Transformed*, the dimension *data management* states that the organization is effective at sharing information and insights. Elsa and Xiaomeng (2022 proposed a business intelligence & analytics maturity model for higher education with five maturity levels. Five out of 18 dimensions are related to the "*people*" category and include: different types of users and their access to the system, the share of active users, users' skills in tools and data literacy, the extent to which a data-driven culture for decision making is encouraged, and level of business intelligence & analytics training. Although the model has five dimensions related to people, none capture how well a team collaborates when using business intelligence & analytics.

In a recent study (Davenport 2022), 25 Chief Data Officers (CDO) were interviewed about key activities and challenges in their work. Establishing a data-driven culture was perceived as one of the respondents' greatest challenges. One respondent described that they tried to assess the change to a data-driven culture in teams by observing what type of questions people asked in meetings. Our matrix could be used as a complementary tool for CDOs to assess the maturity of data-driven culture in teams. The matrix can also be used as a self-assessment by a team. The assessment's outcome can indicate if analytical skills need to be improved via, e.g., programs in data literacy or if group collaboration needs to be improved. The work of Wheelan (2016 provides an extensive set of recommendations on how group development can be improved. To the best of our knowledge, similar extensive set of recommendations for analytics is not available.

If we apply the suggested matrix to the situation in Fortune 1000 organizations, it implies that roughly 20% of the organizations are in the quadrant of data-driven culture, and the remaining 80% are skilled in advanced analytics and have not established a data-driven culture. According to our matrix, these organizations should focus on improving group collaboration instead of polishing their skills in analytics.

Conclusions

In this paper, we investigated how maturity in data-driven culture can be assessed in a team.

The significance of our research is that it synthesizes previous work in analytics and group development, topics that have been studied separately in the literature. In particular, we have developed a matrix for assessing the maturity of data-driven culture in a team. The matrix is based on two pillars: i) maturity in analytics, and ii) how well a group of people can collaborate. For this paper, we reused Wheelan's work for assessing and improving group development. An organization that is more familiar with another group development model, e.g., Tuckman's stages of group development (Tuckman 1965), can rather straightforwardly replace the model of Wheelan (2016.

It is well-known in the literature (Davenport and Bean 2018; Halper and Stodder 2017; LaValle et al. 2011) that organizations are struggling to overcome nontechnical factors to establish a data-driven culture. This is in contrast to the research community's focus on investigating the (positive) effects that a data-driven culture has on different domains, Table 1. Given this mismatch between the perceived barriers in practice and current research focus in academia, we argue that a new line of research needs to be opened to help organizations overcome or reduce the major nontechnical barriers. The matrix we developed for assessing maturity in data-driven culture in a team is one piece of the puzzle to address the nontechnical barriers.

Based on the findings from the literature survey and the answers from the BI & Analytics consultants, we can derive an initial draft that describes the characteristics of a team that has established a data-driven culture:

- All members have a brief understanding of what is meant by business intelligence & analytics, data-driven organizations, and good skills in data literacy, Figure 7 .
- Some team members have good skills in the different types of analytics and associated tools, Figure 7.
- Good group development is present, Figure 8, Figure 9.
- Analytics is frequently used when making decisions, (Gupta and George 2016; ZareRavasan 2021).

The limitation of the above list of characteristics is that it is influenced by the culture of BI & Analytics consultants in one particular company. Additional investigations in other organizations need to be done before any general conclusions can be drawn.

Finally, we intend to collect experiences of using the matrix in practice and relate the findings to suitable models in organizational culture (Leidner and Kayworth 2006), e.g., the Competing values model (Quinn and Rohrbaugh 1983).

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