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**Article**

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# Assessing Maturity in Data-Driven Culture

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## ABSTRACT

Research on assessing a group's maturity in data-driven culture is rare and fragmented. This article investigates how maturity in data-driven culture can be assessed from a historical perspective. A case study was done on how the Education Council evolved in analytics maturity and as a group during 2014-2023. The assessment showed that the Education Council experienced both successful progression of group development and usage of analytics, as well as regression in group development and analytics usage. The practical implications of the findings are that group leaders need to be aware of the interplay between analytics usage and group development when planning to improve their group's maturity in data-driven culture.

## KEYWORDS

analytics, Data-driven culture, group development, maturity model

## 1. INTRODUCTION

Organizations that frequently use analytics (derive insights from collected data) to gain competitive advantages are often top performers in their business (Davenport & Harris, 2017; McAfee & Brynjolfsson, 2012). This is in contrast to organizations that mostly make decisions based on gut feeling or rarely use computerized decision support systems; these organizations are rarely classified as top performers in their business. Hence, many organizations try to increase their usage of analytics to become top performers in their business (e.g., transportation, manufacturing, higher education, and health care).

However, not all organizations manage to increase their usage of analytics and become data-driven. It is well-known in the literature that most of the common pitfalls for introducing and using analytics are non-technical, e.g., lack of support from management, lack of skills, poor data quality, or resistance among employees (Berndtsson, Lennerholt, Svahn, & Larsson, 2020; Davenport & Bean, 2018; Halper & Stodder, 2017; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011).

Establishing a data-driven culture where a group of people frequently and openly discuss insights from collected data is problematic. For example, the share of Fortune 1000 organizations that claimed they had managed to establish a data-driven culture has steadily declined from 28,3% in 2019 to 20,6%

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in 2023, and the major underpinning barriers are *people, culture, and process* (NewVantagePartners, 2023). This means that roughly 80% of Fortune 1000 organizations are struggling with establishing a data-driven culture in their teams, despite having advanced analytics (e.g., data mining, artificial neural networks, rule systems) in place.

The literature assessing a group's maturity in data-driven culture is fragmented and rare. A large number of maturity models in business intelligence & analytics have been proposed in the research literature and by practitioners, e.g. (Eckerson, 2009; Elsa & Xiaomeng, 2022; Halper & Stodder, 2014; Lahrmann, Marx, Winter, & Wortmann, 2011; Lismont, Vanthienen, Baesens, & Lemahieu, 2017). The limitation of existing maturity models in business intelligence & analytics is that they mainly target the organizational level and rarely assess the group level. In Davenport (2022), one of the interviewed Chief Data Officers said that they assessed the shift to a data-driven culture in groups by observing whether people asked analytics-related questions in meetings, e.g., "What does the data tell us? Do you have data to support that hypothesis?".

A group's success also depends on how well members collaborate. Previous work has investigated relationships between group development and maturity in a specific domain. Gren, Torkar, and Feldt (2017) used the group development model by Wheelan (2016) to investigate the performance of agile teams. Similarly, Guttenberg (2020) used the model by Tuckman and Jensen (1977) to investigate the performance of Lean Six Sigma projects. In addition, Edmondson (2018) argues that psychological safety is crucial for groups to be successful.

A matrix for assessing maturity in analytics and group development was recently proposed by Berndtsson and Svahn (2022). The matrix is based on progression in analytics (Watson, 2013) and progression in group development (Wheelan, 2016). Similar to any maturity model, the matrix provides a snapshot of the current maturity state.

The objective of this paper is to investigate how the matrix suggested by Berndtsson and Svahn (2022) can be used for assessing maturity in data-driven culture from a historical perspective, and to reflect on how external influence effected the groups maturity, in this case the lack of physical meetings due to the Covid-19 pandemic. The historical assessment can then be used as a starting point for making suitable improvements.

The remainder of this paper is structured as follows. Section 2 introduces the related background in data-driven organizations and group development. Section 3 presents the research approach. Section 4 presents a narrative storyline for the chosen case. Section 5 presents an in-case analysis. Section 6 discusses related research, and conclusions are presented in Section 7.

## 2. BACKGROUND

This Section will introduce data-driven organizations, group development, and the matrix for assessing maturity in analytics and group development.

### 2.1 Data-Driven Organizations

A data-driven organization is an organization that emphasizes collecting and analyzing data to make better decisions by using analytics (Anderson, 2015; Halper & Stodder, 2017). Organizations that characterize themselves as data-driven are frequently business leaders (McAfee & Brynjolfsson, 2012). In a recent study of over 30 000 American manufacturing companies, the finding was that " .. *productivity was significantly higher among plants that use predictive analytics …. compared to similar competitors*." (Brynjolfsson, Jin, & McElheran, 2021). It is estimated that roughly a third of the organizations make a successful shift and become data-driven (Bean & Davenport, 2019; Halper & Stodder, 2017). The majority of organizations struggle with barriers that are non-technical, e.g., resistance among employees, lack of skills, and lack of strategies.

Boyd (2012) defined analytics as "*the scientific process of transforming data into insight for making better decisions*", and it can be categorized into (Delen & Ram, 2018):

- **Descriptive analytics** investigates the past, typically by a data warehouse solution.
- **Predictive analytics** (also referred to as data mining) investigates the near future and can be categorized into (Turban et al., 2015) prediction, association, and clustering.
- **Prescriptive analytics** investigates decision recommendations, e.g., by using expert systems or decision trees.

Predictive and prescriptive analytics are also referred to as advanced analytics. When analytics is frequently used within an organization in a group for decision-making, a data-driven culture is said to emerge. Samples of definitions of a data-driven culture are provided in Table 1.

All definitions in Table 1 share an underpinning assumption that data-driven decision-making is part of the norm and behavior among a group of people. An important aspect of the definition is the frequency (extent, degree) of using analytics (Berndtsson & Svahn, 2022; Gupta & George, 2016; ZareRavasan, 2021). Similarly, LaValle et al. (2011) found in their investigation that top performers used analytics to guide decisions twice as much as lower performers.

## 2.2 Group Development

It is well-known in the literature that a group typically evolves in different phases and two classical models are Tuckman's group development model (Tuckman, 1965; Tuckman & Jensen, 1977) and the Integrated Model of Group Development (IMGD) by Wheelan (2016).

Tuckman (1965) proposed a model consisting of four stages:

- **Forming**. The first stage is characterized by a lack of clarity regarding roles, purpose, and objectives. Group members try to learn about each other to form opinions about other group members.
- **Storming**. The second stage is characterized by debates and arguments that question the structure of the group, progress of objectives, and leadership.
- **Norming**. In the third stage, group members establish norms for how the group will collaborate and address objectives. The leader of the group is usually accepted and respected at this stage.

**Table 1. Sample definitions of data-driven culture**

| Reference | Definition |
|---|---|
| (Berndtsson & Svahn, 2022) | 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. |
| (Gupta & 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. |
| (Kiron, Shockley, Kruschwitz, Finch, & Haydock, 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. |
| (Medeiros & Maçada, 2022) | 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. |
| (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. |

- **Performing**. In the fourth stage, the group has a clear focus on the task that needs to be done and uses each other's strengths to complete the task with high quality.

Wheelan (2016) integrated earlier group development models, e.g., (Tuckman, 1965), with personal experience and suggested four phases of group development:

- **Dependency & Inclusion**. In the first stage, group members try to establish membership, safety in the group, purpose, and future activities. The leader is rarely challenged at this stage.
- **Counter-Dependency and Fight**. In the second stage, conflicts and debates start to arise regarding purpose, roles, future activities, and leadership in the group.
- **Trust and Structure**. In the third stage, the group has evolved into more open communication, based on trust and structure.
- **Work and Productivity**. In the fourth stage, the group focuses on completing tasks with high quality.

The work of Wheelan (2016) includes recommendations for how to assess group development maturity and activities for improving group development. In addition, more recent work on psychological safety (Edmondson, 2018) in groups provides additional recommendations for how to improve group dynamics.

## 2.3 Assessing Maturity in Analytics and Group Development

Maturity models are commonly used to assess to what extent a concept, e.g., business intelligence & analytics, has been adopted in an organization. Typically, a maturity model is divided into stages of progression, e.g., nascent, early, established, mature, and advanced/visionary (Halper, 2022). For each stage, a given set of dimensions are assessed, e.g., organizational factors, data infrastructure, analytics, governance (Halper, 2022). According to by Berndtsson and Svahn (2022), existing maturity models in business intelligence & analytics have limited support for assessing maturity in data-driven culture. Main reasons are that progression in group development is missing. To assess maturity in data-driven culture, some organizations have started to observe what type of questions people ask in meetings (Davenport, 2022).

The maturity model (matrix) by Berndtsson and Svahn (2022) focuses on assessing a group´s maturity in data-driven culture, and should be used as a complement to existing maturity models in business intelligence & analytics. As can be seen in Figure 1, the matrix combines analytics maturity with group development. Progression in analytics if described as a ladder with descriptive analytics, predictive analytics, and prescriptive analytics (Watson, 2013). Similarly, progression of group development can be described by the group development stages of Wheelan (2016).

**Figure 1. A matrix for assessing a team's maturity in data-driven culture (Berndtsson & Svahn, 2022)**

| | | 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 | | | | |

According to Berndtsson and Svahn (2022), the matrix can be divided into three categories:

- **Territorial analytics (white area)**: This category represents a team that is in the early stages of group development but frequently uses analytics to derive insights from data. Although analytics is frequently used, findings are seldom openly shared with other members.
- **No analytics (grey area)**: This category represents a team that evolves as a group and becomes successful without frequently using analytics.
- **Data-driven culture (green area)**: This category represents a team that has established trust & structure and is considered a high-performance team. Analytics is frequently used when making decisions. All members have a brief understanding of what is meant by business intelligence & analytics, data-driven organizations, and good skills in data literacy. Some team members have good skills in the different types of analytics and associated tools.

The work of (Berndtsson & Svahn, 2022) provides few explicit guidelines on how to progress between the different stages of analytics or group development. Although detailed guidelines for progressing in group development exists, e.g., (Edmondson, 2018; Wheelan, 2016), similar guidelines for progressing in analytics (from a sociotechnical perspective) are rare. However, recent work on data storytelling (Dykes, 2020), data democratization (Yaffe, 2020), and data literacy (Sternkopf & Mueller, 2018) are likely to fill this gap in the future.

## 3. RESEARCH APPROACH

For this research, a case study approach (Yin, 2014) was chosen since we explore how to assess maturity in data-driven culture in a group from a historical perspective. In particular, we use the matrix suggested by Berndtsson and Svahn (2022) and develop a process for using the matrix from a historical perspective.

### 3.1 Case Selection and Setting

The selected case was an Education Council at a University. The Education Council was re-established at the beginning of 2014. Before 2014, the Education Council had had three different phases that can be categorized into:

- **Pioneers** (~2002-2005), the first version of the Education Council, consisted of programme leaders and a local student adviser. Most of the work was focused on developing routines and processes for student recruitment, course quality, and student administration.
- **Philosophers** (~2006-2009), the second version of the Education Council consisted of subject leaders that had more discussions around strategic and philosophical questions than the first version of the Education Council.
- **Management** (2010-2013), the third version of the Education Council, consisted of subject leaders and was chaired by the heads of Schools. Most items on the agenda were related to discussing important documents, evaluations, and strategies.

During the last two phases of the Education Council, programme leaders and subject leaders worked mainly together in isolated clusters, but no real collaboration between programme leaders took place on a school wide level. Still, all subjects came out with flying colours in the national quality evaluations that took place from 2011-2013.

According to the head of school (back in 2014), there were three main reasons for re-forming the Education Council:

- **Academic leadership**. The University at large and the school had a track record of strong line management. There is always a dilemma and debate on how much should line management be involved in academic related decisions, e.g., how to improve quality in courses, and how to balance line leadership vs academic leadership. Hence, in order to avoid a too strong role of the line management in the Education Council – since the council's main object is academic and educational areas – it was decided that the academic leaders should play a more prominent role.
- **A school-wide forum**. A forum for sharing school-wide insights among programme leaders and subject leaders was necessary to establish since insights and good practices were usually only shared within a sub set of programme leaders and subject leaders and not with the whole school.
- **Isolated sub cultures**. In 2014, the school had 14 undergraduate programmes and two master programmes, covering a large spectrum of subjects from computer science, information systems, user experience design, to game development. Given the size of the school – with roughly 120 employees and 1200 students, different clusters of programmes (and associated teachers) were located in different buildings. As with most things located in physically different locations, things will over time start to evolve in divergent directions.

In 2014 the school underwent a major reorganisation that stirred up emotions among employees. Furthermore, the programme leaders had not been part of any major school-wide councils since 2005/2006. Hence, when the invitation to the first meeting of the Education Council was sent out in 2014, the programme leaders came to the first meeting with their own sub cultures and, in some cases, with a big frustration why they now had to adapt to something new, and also be pulled away from teaching, to yet another meeting. Their line of argument was that, they had just recently passed a national evaluation, so that was hard evidence that their current way of working was the right approach.

The current version of the Education Council focuses on quality-related aspects related to undergraduate and master level at a school wide level. Examples of work tasks include: monitoring key performance indicators (KPI), collaborating with administrative units (e.g., student support, library, admission office), and quality assessment of education. The 27 members of the Education Council represent three different categories of responsibilities within the school and the university: i) study program leaders and subject leaders, ii) heads of department, and iii) support areas (e.g., staff members working with international studies, student counseling, and equality). The big majority of members were study program leaders and subject leaders that teach in subjects such as computer science, information systems, cognitive science, computer game development, and media arts. Roughly 60% of the members have a Ph.D. degree. The Education Council has monthly meetings led by a chairman and a vice-chairman (both are subject leaders) that report to the head of the School and the board of the School.

In 2014 the university did not have any business intelligence & analytics solution in place. Data from various databases were mainly put together in Excel and visualized in tables or simple bar charts. Thus, there were no expectations from the University or the School that the work in the Education Council should rely on business intelligence & analytics.

### 3.2 Data Collection Methods

The research approach for data collection was a mix of ethnographic studies, document studies, and interviews.

The authors have been chairman and vice-chairman of the Education Council during 2014-2022. Hence, we have been extensively involved in the Education Council. According to Myers (1999), an ethnographic approach is suitable when the researcher is extensively involved in the group under study. We have rich data collection through personal observations and internal meeting notes.

A narrative storyline (3600 words) of how the Education Council evolved during 2014-2018 was developed from personal observations, internal meeting notes, and official documents. The narrative storyline was used as a basis for four semi-structured interviews (two study program chairs and two support area staff) that had been part of the Education Council for the entire period. The interviews were done in 2019 and each interview lasted approximately 45-60 minutes. None of the respondents had any objections to the documented events in the narrative storyline.

### 3.3 Data Analysis

Each year of the narrative storyline was analyzed by the authors with respect to maturity in group development and analytics. For assessing group development we used the model by Wheelan (2016), and for assessing analytics maturity we used the characteristics of a data-driven culture as described in (Berndtsson & Svahn, 2022):

- All members have a brief understanding of what is meant by business intelligence & analytics, data-driven organizations, and good skills in data literacy.
- Some team members have good skills in the different types of analytics and associated tools.
- Good group development is present. (overlap with the model by Wheelan (2016))
- Analytics is frequently used when making decisions.

## 4. NARRATIVE STORYLINE

This Section presents a reduced version of the narrative storyline that was used in the interviews. The narrative storyline has been complemented with details on how KPI data was collected and presented.

### 4.1 2014

The two first monthly meetings (February and March), were held in an ordinary class room, with the head of school present. The meetings were spent on discussing the purpose and tasks of the new version of the Education Council, and trying to get a basic grip on school-wide key performance indicators.

The classroom imposed a top-down leadership, where the chairman was in front of the class (group members) and was giving a lecture. Furthermore, as the head of school was present in the meetings, all programme leaders paid close attention to what the head of school did, and much less to the newly appointed chairman and vice chairman of the Education Council. Resistance and frustration to changing to a new and unknown phase, was very much present in the discussions.

After the first two meetings, the Education Council moved to a room, where the chairs and tables were placed in a U-shaped formation. This removed the feeling that the chairman was in front of the members and telling them what to do. In addition, the head of school no longer participated in the meetings.

At the third meeting (April), the chairman and vice chairman did a personal presentation of their academic background and spare time interests. The spare time interest was deliberately part of the presentation, as a way to build trust, and it worked to some extent. This meeting also set the scene for how the Education Council should work in practice, e.g., having individual dialogue meetings with each programme leader after each semester. Still, frustration boiled up regarding: i) the amount of work that programme leaders were expected to do, ii) how programme leaders should prioritize their tasks, and iii) serious collaboration problems with the centrally located student support unit.

At the end of the spring semester in June, the chairman and vice chairman conducted individual dialogue meetings with each programme leader, regarding the status of courses and students in their respective programmes. Each meeting lasted roughly 1.5 hours.

To improve the collaboration with the centrally located student support unit, the school's centrally located student advisor was added as a permanent member to the Education Council.

During the fall of 2014, the Education Council discussed and shared insights regarding: i) the previous batch of final year projects, ii) internationalisation, e.g. offering courses in English, and iii) launching new study programmes.

During October, the chairman and vice chairman had a first meeting with an external leadership consultant, that discussed both basic leadership aspects such as the importance of establishing trust, and setting a vision, but also current dilemmas when running the Education Council.

At the end of the fall semester, a 2nd round of dialogue meetings with the programme leaders were done, and summaries from each dialogue meeting was displayed on the wall at the next meeting in the Education Council.

The first year was concluded by a report that documented all the activities for 2014 and presented an overview of school-wide key performance indicators. Visualization of school-wide KPIs was mainly visualized by line charts, showing the evolution of KPIs for the last five years. Wherever suitable, each KPI was segmented into study programs or subjects. At this stage, the KPIs were put together by collecting data from program chairs and the central administration of the university.

### 4.2 2015

During spring, each member was asked to do a mini-presentation during 15-20 minutes in terms of three slides: i) academic background, ii) hobbies, and iii) geek-level expertise. The intention was to use the mini-presentations as a mechanism to establish trust within the group. The reactions to having mini-presentations were mixed. Some members went all in and presented several unique and unknown skills that they had. Other members, thought the activities were "cheesy" and lame, especially when, the chairman and vice chairman talked about how the mini-presentations could be linked to leadership and building trust. The word was soon out among other teacher groups that the Education Council was doing cheesy mini-presentations, instead of discussing real problems.

In 2015, the School put 14 new goals and key performance indicators in place for education. Some of the new KPIs were more qualitative in their nature and could not easily be assessed. Instead, each program leader was asked to give an estimation of the status. The new school-wide key performance indicators caused several discussions on how quality in education could be assessed. On more than one occasion, members raised a statement that "this is not how we can improve quality in our education", i.e., looking at key performance indicators was useless for improving quality improvement.

A wheel of routine activities was now emerging for the Education Council:

- Activities for recruiting new students
- Reflections on the number of student admissions
- Lessons learned from previous batch of final year projects
- Dialogue meetings with programme leaders after each semester

At the beginning of the fall semester of 2015, it was announced that all education at the university was to be assessed by an external expert committee during the spring semester of 2016. According to the time table, the Education Council had roughly nine months to collect data and prepare a report. The evaluation report was built around a SWOT-table and reflections on a given set of aspects such as internationalization, pedagogical development, and relationship to job market. Much of the data for the report was collected by the aid of discussions that the programme leaders held and summarized.

Programme leaders were now offered to participate in a one-year leadership training (five sessions) during 2015/2016.

The year was concluded with dialogue meetings and an annual report for 2015, including how the School measured up against the KPIs that were launched earlier during the year. Similar to previous year, the school-wide key performance indicators were put together by collecting data from program chairs and the central administration of the university. The new school-wide KPIs implied more reporting by using tables and text, since graphical visualization was not suitable.

### 4.3 2016

The beginning of 2016 was dedicated to finalizing the evaluation report, together with the head of School. At the end of April, the expert panel arrived and held several meetings with students, members of the Education Council, and line management of the School. The meetings went well, and the closing comment from the chair of the expert panel, at the one of the meetings with members from the Education Council, made our day: “Despite the broad range of programmes, you all seem to be working and thinking in great harmony.” When the final written report arrived from the expert panel, none of the programmes or study subjects at our School had received criticism with respect to poor quality.

In order to assess the discussion climate within the Education Council, members were asked to answer (anonymously) two questions:

- I trust how the chairman and vice chairman lead and develop the Education Council.
- I have the opportunity to influence decisions that are made in the Education Council.

The members were asked to give their answers by using a Likert scale: strongly disagree (1) up to strongly agree (6). We received 17 results out of roughly 25 possible, as described in Figure 2 and Figure 3.

In 2016 the Education Council started to rank all the course evaluations, based on the overall course grade that the students had given each course, and displayed an overview graph at a staff meeting. The purpose was to get an overview of how much student frustration there was in the courses. That is, a high grade meant that students were happy with the course, and a low grade meant that students were frustrated over something in the course. If a course had an overall grade below a certain threshold, then the course responsible and responsible subject leader needed to have a meeting about how the course responsible had perceived the course. This was received by the staff with mixed emotions, but the dialogues were useful for making improvements.

**Figure 2. I trust how the chairman and vice chairman lead and develop the Education Council**

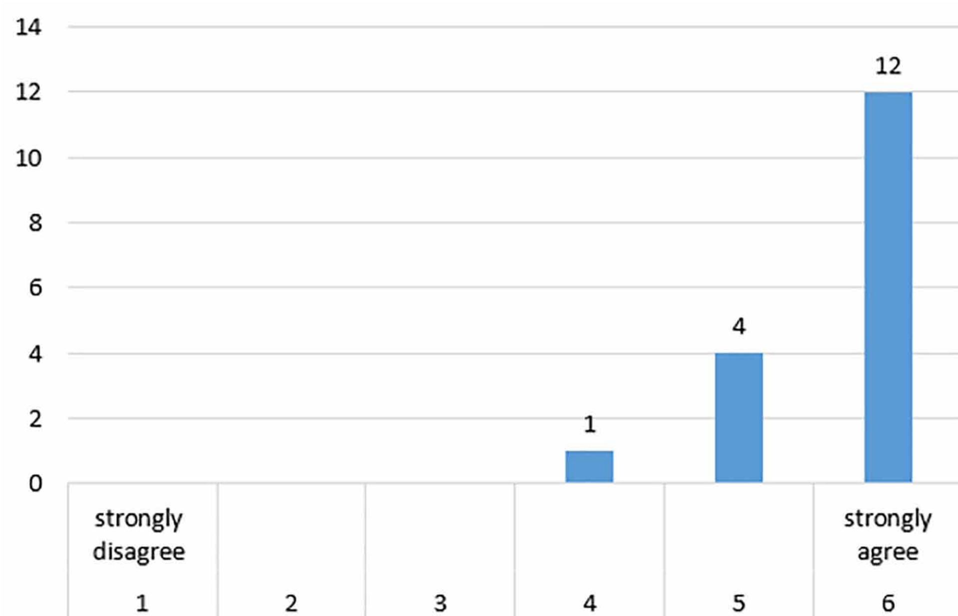
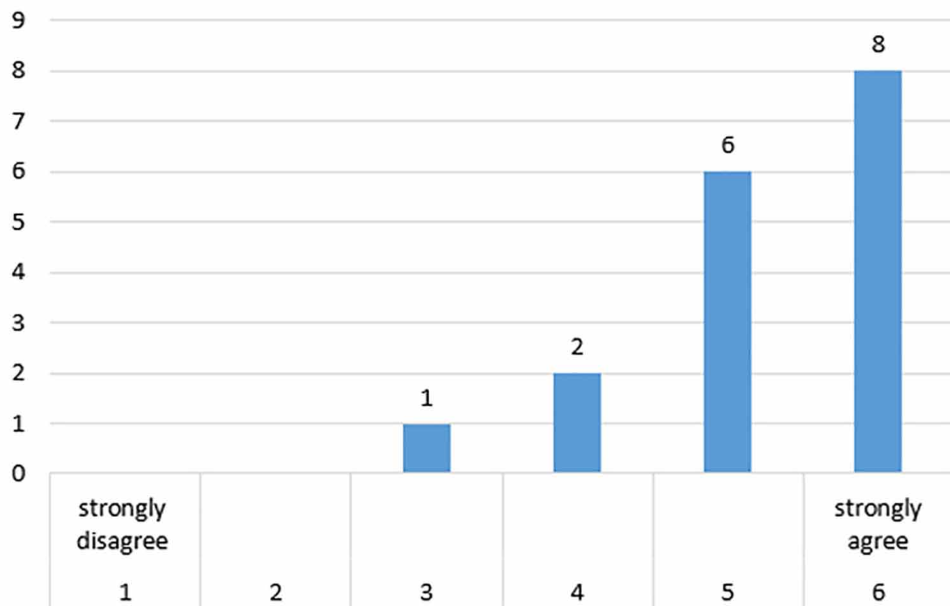


Figure 3. I have the opportunity to influence decisions that are made in the Education Council




During the fall semester, the Faculty board requested input on a new quality assessment system. The Education Council submitted a detailed response describing the established wheel of routine activities and how analytics was frequently used to support the activities. Included in the response was a request to implement a university-wide business intelligence & analytics solution, e.g., data warehouse and dashboards.

Similar to the previous year, the school-wide key performance indicators were put together by collecting data from program chairs and the central administration of the university.

### 4.4 2017

The previous 14 KPIs that were launched by the School in 2015 were now up for discussion due to a new version of long-term development plan for the School. As a response, the Education Council developed nine KPIs that were closely related to the mission of the Education Council. Whenever possible, each KPI was segmented into different programs, sorted, and comparisons were provided to previous year or a defined target. In addition, long term trends (10+ years) were provided for relevant KPIs. A switch was made to Power BI, which had a more extensive set of visualization options for the collected data.

In 2017, the Education Council was informed that the resources for running undergraduate final year projects in 2018, were reduced by 25%, due to lack of resources (staff & money). As a reference point, in 2017 the School had 209 registered students on undergraduate final year projects, and all of them were done individually. For 2018, the prediction was an increase in number of students by 20-25%. The program leaders solved this task by discussing with their related teachers' groups, how the process of final year projects could be redesigned, in order to compensate for the reduction in available resources. The solutions that came back from the program leaders fell into two categories: i) students were asked to do their projects in groups of 2-3 students, or ii) individual projects with less time for supervisors and examiners.

During the fall semester of 2017, the Education Council did an investigation in *research in education*. The reasons for choosing the theme, were several: i) continue earlier work done during a staff day in 2015, ii) preparation for upcoming quality evaluation, iii) internal quality indicators, and iv) the theme has always been a major assessment criterion in national quality assessments etc.

The Education Council collected data by asking course responsibles to submit examples of research activities in their courses (thesis courses were excluded). Each research activity was classified into four types, and with one sentence for activity description. In addition, course responsibles were asked to submit examples of research coming from our own research groups. In the next step, each program leader compiled a study program specific list in Excel, which was later visualized. At the end of the fall semester, the results were presented at an open Poster session for the entire School. The results covered 147 mandatory courses that students took, before their thesis project, broken down per program. The open Poster session attracted the interest of the University Dean, who took the time to participate in the Poster session.

Similar to previous year, the school-wide key performance indicators were put together by collecting data from program chairs and the central administration of the university.

### 4.5 2018

A new university-wide quality assessment system was released in early 2018. Unfortunately, the quality assessment system was not based on a business intelligence & analytics solution as the Education Council requested in 2016. Instead it was based on submitting annual reports describing quality improvement tasks.

Most activities during 2018 followed the yearly cycle of dialogue meetings, marketing and open house, final year projects, and a dedicated investigation during the fall semester. For the fall semester of 2018, the Education Council decided to do a black box investigation for each program. The investigation was done as a preparation for an upcoming quality evaluation. The black box investigation was done, in order to see if the courses within each program, still were nicely connected to each other.

Similar to previous year, the school-wide key performance indicators were put together by collecting data from program chairs and the central administration of the university.

### 4.6 Epilogue 2023

After 2018 the Education Council went through several changes. The chairman stepped down and left the Education Council. A new chairman (previous vice-chairman) and vice-chairman (previous member) were appointed. Approximately 25% of the members were replaced with new members. This is in contrast to 2014-2018 when roughly 1-3 members were replaced each year. Due to the Covid-19 pandemic, all meetings switched to online meetings. As a consequence of switching to online meetings, group members became more reactive rather than proactive. The previous focus on increasing analytics faded away. A university-wide business intelligence & analytics solution is still not available.

The epilogue was not part of the narrative storyline for 2014-2018 that we used for the interviews. Hence, it should be viewed as our personal reflection on what happened in 2019-2023.

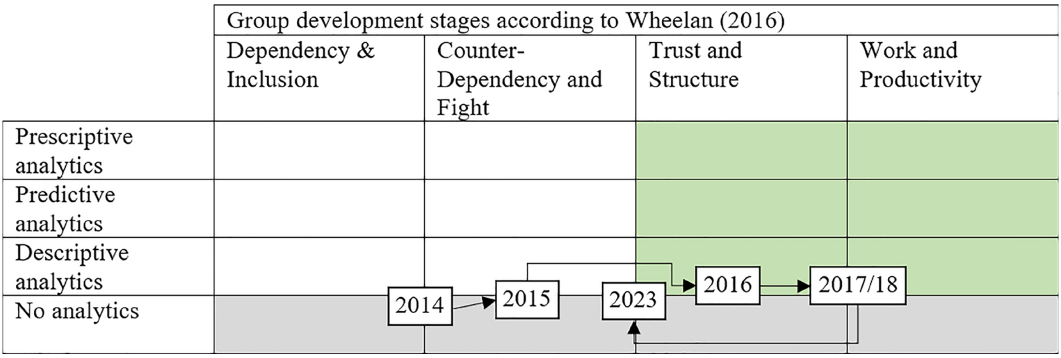
## 5. ANALYSIS

Figure 4 presents an overview of how the Education Council evolved in analytics maturity and group development 2014-2023.

Our assessment for 2014-2023 are as follows:

- **2014**: Purpose of Education Council defined, frustration, focus on building trust, early attempts to use descriptive analytics on a Schoolwide level, Excel and Pivot Tables. Our estimation is that the Education Council matches the transition from stage 1 to stage 2 in Wheelan's model. The group matched one of the analytics characteristics, i.e., some team members have good skills in the different types of analytics and associated tools, as described in (Berndtsson & Svahn, 2022).

**Figure 4. Progression of analytics and group development**




- **2015**: Focus on building trust, leadership training, wheel of routine activities emerges, increased usage of descriptive analytics. Our estimation is that the Education Council matches stage 2 in Wheelan's model. The group matched one of the analytics characteristics, i.e., some team members have good skills in the different types of analytics and associated tools, as described in (Berndtsson & Svahn, 2022).
- **2016**: External expert panel, discussion climate assessed, wheel of routine activities established, frequent usage of descriptive analytics. Our estimation is that the Education Council matches stage 3 in Wheelan's model. The group matched two of the analytics characteristics, i.e., i) some team members have good skills in the different types of analytics and associated tools, ii) frequent usage of analytics, as described in (Berndtsson & Svahn, 2022).
- **2017**: Data collection and analysis on research in education, poster presentation with University Dean, switch to Power BI. Our estimation is that the Education Council matches the transition between stage 3 and stage 4 in Wheelan's model. The group matched two of the analytics characteristics, i.e., i) some team members have good skills in the different types of analytics and associated tools, ii) frequent usage of analytics, as described in (Berndtsson & Svahn, 2022).
- **2018**: Black box investigation of courses in programs, good grasp of schoolwide indicators for education. Our estimation is that the Education Council matches the transition between stage 3 and stage 4 in Wheelan's model. The group matched two of the analytics characteristics, i.e., i) some team members have good skills in the different types of analytics and associated tools, ii) frequent usage of analytics, as described in (Berndtsson & Svahn, 2022).
- **2023**: Changes in leading positions, 25% of members replaced, members became more reactive due to Covid-19, focus on using analytics faded away. Our estimation is that the Education Council matches the borderline between stage 2 and stage 3 in Wheelan's model. The group matched one of the analytics characteristics, i.e., some team members have good skills in the different types of analytics and associated tools, as described in (Berndtsson & Svahn, 2022).

The overall trend of the Education Council for 2014-2018 was incremental steps that primarily followed the progression of the group development stages of Wheelan (2016) with some progression in analytics. A regression in group development and analytics occurred in 2019-2023. This was due to the replacement of members, switch to online meetings (due to Covid-19), and less focus on maintaining the level of analytics. The switch to online meetings made previous group discussions more difficult, and members became more reactive (rather than proactive) than before Covid-19.

The usage of descriptive analytics in the early years (2014-2015) was mostly focused on getting a basic grip on school-wide key performance indicators. During 2016-2018 the frequent usage of descriptive analytics in meetings acted as a catalyst for group development. Whenever data was visualized, it automatically generated discussions: how had the data been collected, when was the data collected, how had the data been analyzed, what is the long-term trend, what is the prediction of the near future (given the current trend), what type of insights can be drawn, and what type of actions should we take? As time progressed, there were fewer personal anecdotes and sweeping comments in the meetings. However, whenever something was sorted or ranked, territorial analytics emerged. In general, the increased usage of analytics improved understanding of the current situation, long-term trends, and what actions need to be taken.

Using the matrix in (Berndtsson & Svahn, 2022) in retrospective helped us to understand how the Education Council evolved in group development and analytics maturity. It has also acted as a reminder that maturity in group development and analytics can quickly deteriorate. The Education Council never matched the analytics criteria, *all members have a brief understanding of what is meant by business intelligence & analytics, data-driven organizations, and good skills in data literacy*, in (Berndtsson & Svahn, 2022). Main reasons for this were lack of resources and no incentives for pushing this into the agenda of the Education Council.

We conclude that the matrix in (Berndtsson & Svahn, 2022) can be used in retrospect by following the following process:

1. Collect historical data, e.g., agendas, meeting notes, and related documents published by the group.
2. Develop and validate a narrative storyline. The narrative storyline will provide context to what happened.
3. For each year, assess group development maturity, e.g., (Wheelan, 2016), and analytics maturity in the group, e.g., (Berndtsson & Svahn, 2022).

Our historical assessment would not have been possible to do without the annual reports and internal meeting notes of the Education Council. We conclude that the matrix should be used as a complementary (rough) estimation of maturity in data-driven culture for a group of people.

## 6. DISCUSSION

It is well-known in the literature that it is difficult to establish a data-driven culture within an organization due to the mostly nontechnical barriers (NewVantagePartners, 2023). According to the literature (Gupta & George, 2016; Herden, 2020; Kiron et al., 2012), having a data-driven culture in place implies that a group of people frequently use analytics in decision-making and are willing to share their data and findings.

Research on how to establish a data-driven culture in groups is fragmented and has mainly focused on encouraging group members to asking the right analytical questions (Watson, 2016), using interactive tools (Wixom, Yen, & Michael Relich, 2013), or using enablers such as self-service business intelligence (Alpar & Schulz, 2016), data literacy (Bhargava & D'Ignazio, 2015), data-driven storytelling (Dykes, 2020), or data democracy (Yaffe, 2020). These recommendations and enablers are good; however, they tend to assume that good group collaboration is already present.

Previous research on group development has often focused on investigating relationships between group development and maturity in a specific domain, e.g., agile teams, or Lean Six Sigma project teams. Gren et al. (2017) investigated the relationship between group development and group maturity when building agile teams. They identified "*… a large overlap between how agile teams are described by practitioners and how high performing teams are described in social psychology*". Similar to our work, Gren et al. (2017) used the IMGD-model by Wheelan (2016) to assess group development. Guttenberg (2020) investigated the relationship between Lean Six Sigma project teams that had used Tuckman's group development model (Tuckman & Jensen, 1977) and those that had not. The conclusion from the investigation was that Lean Six Sigma project teams that had experience of Tuckman's group development model had better performance than similar teams that had no experience with Tuckman's group development model. We agree with Gren et al. (2017) and Guttenberg (2020) that experience of a group development model is fundamental for establishing a successful team, regardless if the team's focus is software engineering, Lean Six Sigma, quality in education, or analytics. We have not come across any literature within group development that discusses business intelligence & analytics.

Related maturity models can assess either maturity in business intelligence & analytics (Elsa & Xiaomeng, 2022; Lahrmann et al., 2011) or in group development (Wheelan, 2016). Hence, they are not optimal to use when assessing how people use analytics in practice. Some organizations are trying to assess maturity in data-driven culture by observing how groups use analytics in practice (Davenport, 2022).

We successfully used the matrix and associated characteristics of what is meant by a data-driven culture (Berndtsson & Svahn, 2022) for assessing how the Education Council evolved during 2014-2023. To the best of our knowledge, our investigation was the first practical use of the matrix and the associated characteristics. We have not come across any similar research (or tools) that have empirically investigated the interplay between analytics and group development.

## 7. CONCLUSION

In this article, we presented a case study of how an Education Council evolved in analytics maturity and as a group during 2014-2023. The assessment showed that the Education Council experienced both successful progression of group development and usage of analytics, as well as regression in group development and analytics usage.

The significance of our research is that we tested and extended the original (conceptual) matrix by a three-step process for using the matrix from a historical perspective. In particular, the narrative storyline is a crucial component for providing context to the maturity assessment.

Practical implications of our research are that group leaders need to be aware of the interplay between analytics usage and group development when planning to improve their group's maturity in data-driven culture. Our finding is that an increased usage of analytics can act as a mechanism in group development to kick-start discussions and reduce the number of anecdotal stories and sweeping personal statements. Similarly, a group that intend to establish a data-driven culture need to spend resources on group development activities, otherwise we believe they will be stuck in territorial analytics.

Limitations of this research are two-fold: single use case and involvement of researchers. As this paper has reported on a single case within higher education, more case studies need to be done before drawing general conclusions. Although we assume that a similar assessment can be done for other domains, e.g., leadership group within manufacturing, we hypothesize that the findings and lessons learnt can be different from the higher education domain. The authors have been actively involved in the Education Council, which impacts data collection and analysis. To address the bias problem, we have validated the narrative storyline that is the foundation of the analysis with four long-time members of the Education Council.

Future work includes testing the matrix on other groups outside the higher education domain, and developing guidelines for improving maturity in data-driven culture in groups.

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