The Analytics Maturity of Logistics SMEs: **Gaining a deeper understanding**

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In this paper, we propose a userfriendly Maturity Model which can be used for (1) gaining insight into the current state of practice regarding the analytics maturity of companies and (2) to analyze the statistical relationship between the level of maturity and organizational performance. In addition to this, we present the results of our preliminary-study which provides a tentative understanding of the analytics maturity of SMEs in the logistics sector in the Dutch province of Gelderland. Although the small sample size of this preliminary study does not allow any definitive conclusion, the first results reveals a statistically significant positive correlation between analytics maturity and organizational performance.

Introduction

The rapid digitization of our society offers great opportunities for companies to create value. Today's companies have access to unprecedented amounts of data generated by digital footprints and event logs left behind by e.g., machines, equipment, customers and suppliers. This data can, in turn, be used to leverage business decisions and improve performance.

An empirical study by McAfee & Brynjolfsson (2012) indicates that companies relying more on data-driven decision making perform better in terms of productivity and profitability. In addition, Müller, Fay & Vom Brocke (2018) found that (for firms which operate in IT-intensive or highly competitive industries) big data and analytics assets are associated with a productivity increase of 3-7 percent. Their findings are based on an econometric study using detailed data of 814 companies. According to the OECD (2013), the benefits of data-driven decision making in terms of business performance include: (1) enhancing research and development (data-driven R&D); (2) developing new goods and services by using data as either a product or a major input (data products and data-intensive products); (3) optimizing production or delivery processes (data-driven processes); improving marketing through targeted advertisement (data-driven marketing); (4) developing new or improved organizational and management approaches (data-driven organization).

While many large companies have adopted digital and data-driven technologies to enhance their competitiveness, many SMEs are still struggling in becoming more data-driven. Kergroach (2020) states that, despite some innovative start-ups and tech SMEs, there is a large 'missing middle' of more traditional SMEs that are lagging behind. According to the OECD (2019, p.3), laggards 'Ignore the potential benefits in productivity and competitiveness deriving from the adoption of digital technologies, cannot clearly identify their needs, or do not have enough capabilities or financial resources to access and effectively use digital instruments'. In order for a company to become data-driven, it requires certain capabilities. For instance, a deprecated IT infrastructure, inappropriate skills, fragile support from top management, inadequate technologies, blurred strategy to align business and IT strategy and limited financial support are barriers which hinder SMEs from becoming data-driven (Maroufkhani, Ismail & Ghobakhloo, 2020). Considering the role of SMEs as backbone of the economy, the importance of SMEs becoming more data-driven should not be underestimated.

In the study presented in this paper the focus lies on the analytics maturity of SMEs in the logistics sector. The reason for this is twofold. Firstly, the logistics sector is vital to the economic growth and competitiveness of the EU. According to Autio et al. (2020, p.29): 'Efficient logistics connects firms to domestic and international markets in a reliable and cost-efficient manner. Conversely, businesses in countries characterised by low logistics performance face high costs, not merely because of transportation costs, but also because of unreliable supply chains, a major handicap in integrating and competing in global value chains'. Secondly, SMEs in the logistics sector experience barriers which restrict their ability to take up digital innovations (see e.g., EU 2015).

With this in mind, in this paper, we propose a user-friendly Maturity Model which can be used (1) for gaining insight into the current state of practice regarding the analytics maturity of companies and (2) to analyze the statistical relationship between the level of maturity and organizational performance. In addition to this, we present the results of our preliminary-study which provides a tentative understanding of the analytics maturity of SMEs in the logistics sector in the Dutch province of Gelderland.

The remainder of the paper is organized as follows. In section 2 the Maturity Model is presented and explained. Section 3 presents the first empirical results. Finally, this paper concludes with a brief overview of the study and avenues for further research.

Analytics Maturity Model for Logistics SMEs

A maturity model (MM) can be defined as a framework that describes, for a specific area of interest, the typical characteristics at different stages of development. In general, a MM can be used in two ways. Firstly, it can be deployed to assess the maturity of an organization (De Bruin et al., 2005). Secondly, a MM can be used as an 'improvement tool' providing guidelines on how to reach the next, higher maturity level (Fraser et al., 2002).

In the context of this study, the MM is used as a yardstick to (1) assess the 'as-is' situation of SMEs in logistics with respect to their data-drivenness and (2) provide them a (structured) guide on how to improve their level of maturity. In addition to these descriptive and prescriptive purposes, a MM has also the potential to be used as a comparative framework for benchmarking maturity across organizations (e.g., Vezzetti, Violante & Marcolin, 2014). According to De Carolis et al. (2017), from a conceptual perspective, these three purposes can be regarded as interrelated phases within a larger three step 'evolutionary' framework. In the first phase the focus should be on deeper understanding of the current domain situation. Based on a thorough understanding of the current situation the model can evolve into being prescriptive. Finally, to allow for a valid comparison, the model should be applied in a wide range of organizations.

For the purpose of this study, we have reviewed several existing maturity models, and combined their strengths and weaknesses. Our main purpose was to develop a user-friendly instrument which can be used (1) for gaining insight into the current state of practice regarding the analytics maturity and (2) to analyze the statistical relationship between the level of maturity and organizational performance.

After an extensive literature and internet search we ended up with the following three widely used maturity models:

1. INFORMS Analytics Maturity Model (IAMM) (Burciaga, 2013);
2. COEO Data Maturity Assessment (COEO, z.d.);
3. TDWI Analytics Maturity Model (Halper & Stodder, 2014).

A review of these maturity models revealed that:

- The determinants of maturity, by and large, converge.
- The models lend themselves to one-on-one discussions and starting points for bringing about improvements for the individual interviews, but are less apt for use in quick scans and survey settings. Most items are sensitive to subjective interpretation.
- The answering scales are too complex for direct use in survey settings.

Regarding the convergence of determinants of maturity, the three selected models (IAMM, COEO and TDWI) mention organization, culture, (data) management, governance, infrastructure, and capabilities (see table 1.). A closer look at the IAMM shows that all of these aspects fit well within the three pillars of the IAMM.

Table 1 Determinants of maturity

IAMM	COEO	TDWI
Organization	Strategy; Culture; Organization	Governance; Organization
Capabilities	Capabilities	Analytics
Infrastructue	(Aspects of) Capability	Infrastructure; Data Management

A practical advantage of the IAMM is its relatively simple structure: the labels of the three pillars make intuitive sense. The three blocks are subdivided in four items each, that are easy to understand and interpret by repondents.

A disadvantage of the IAMM is that the answering scale is unclear, and makes use of many words to help interviewees score their organization in three levels of maturity (low; medium; and high), although interviewees are allowed to refine their scores on a 10-point scale (1/3 for low; 4/7 for medium; and 8/10 for high).

In contrast, the TDWI model makes use of a simpler answering scale, from nascent to visionary. The TDWI model assumes a chasm in the scale, dividing organizations up to those in the early stages of adoption from those who make consistent use of analytics throughout the organization (see figure 1).

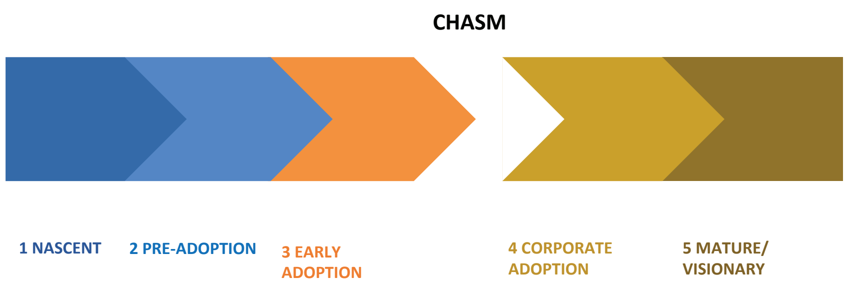

Figure 1 Scale used by the TDWI model

We therefore decided to use the structure of the Informs model (three blocks of four items each) and the TDWI answering scale. The items of the Informs model have been further simplified, and translated into Dutch (as the Netherlands is the primary target market for the Maturity Scan).
The objective of this study was not only to measure maturity per se, but also to analyze the correlation between maturity and organizational performance. Although hard performance indicators are generally preferred, in many settings subjective performance indicators are recommended (Dess & Robinson, 2020). Subjective performance measures provide relevant information in case the set of objective performance data is limited, for example due to the presence of multiple stakeholders with different interests (Vij & Bedi, 2016). Moreover, even if both subjective and objective measures are available, it turns out that the two types of measures are strongly correlated (Santos & Brito, 2012). Also because of the sensitivity of hard performance measures like profit and growth to incidents and events (e.g., the impact of COVID-19 on profit and growth), it was decided to incorporate subjective questions on performance. Five indicators were included: financial performance; growth; customer satisfaction; employee satisfaction; and environment. The five indicators were measured on a 7-point scale, in terms of a comparison against peer companies in the industry.

The questionnaire is developed using Qualtrics. For use in other industries and countries, the questionnaire has been translated into English, using Qualtrics' translation facilities and additional editing. No backtranslation has been carried out at this stage of the research.

Preliminary empirical results

Data was collected with the help of students via telephone interviews with company managers of SMEs in the logistics industry. The students were given background information and clear instructions during a kick-off meeting. During the one-on-one interviews they filled out the Qualtrics Questionaire together with the interviewees. Filling out the questionnaire together allowed the students to clarify the questions in order to make sure the questions were understood as intended. Companies were mainly approached through existing networks of logistics companies in the province of Gelderland (the so-called Logistics Valley). After each interview, the company concerned received a personalized report with their company's scores relative to the market.

We received complete responses to the preliminary study from 40 companies. The logistic companies were located in the region around Arnhem in the province of Gelderland and had around 150 plus employees on average.

The chasm

Using the chasm proposed by the TDWI model, the table below shows the proportions of answers falling in the two top categories, first combined (corporate adoption plus mature/ visionary) followed by the top category (mature/visionary) only (see table 2).

Table 2 Results based according to the chasm approach

	Corporate adoption + mature/ visionary	Mature/visionary
	procent	procent
Organization - People	44	12
Organization - Leadership	47	16
Organization - Measurement	42	16
Organization - Processes	49	19
	45	16
Skills - Governance	47	16
Skills - Specialists	44	19
Skills - Methods and Software	35	14
Skills - Data Quality	40	14
	41	16
Infrastructure - Data Quality	42	16
Infrastructure - Data Access	40	12
Infrastructure - Management	44	12
Infrastructure - Architecture	40	12
	41	13

By and large, the items trigger similar responses. Items on organization have somewhat higher scores. A relatively low score in the skills block is software & methods. In the block on infrastructure, data access and architecture are relatively low. Processes and (counter to expectation) specialists, do well at the highest level of maturity compared to other items.

A measure of perceived (or subjective) performance has been computed as the average of five aspects of performance. The level of internal consistency is acceptable, according to commonly accepted standards (Cronbach's a =.75) and leaving out any of the five items would reduce a.

The distribution of the five performance measures is shown in figure 2. Perceived (hard, financial) performance indicators like profitability and growth are in the full range of the 7-point scale. Customer satisfaction has only one observation below 4, while employee satisfaction has three. None of the respondents gives a score below 3. The median values are 5 for all variables.

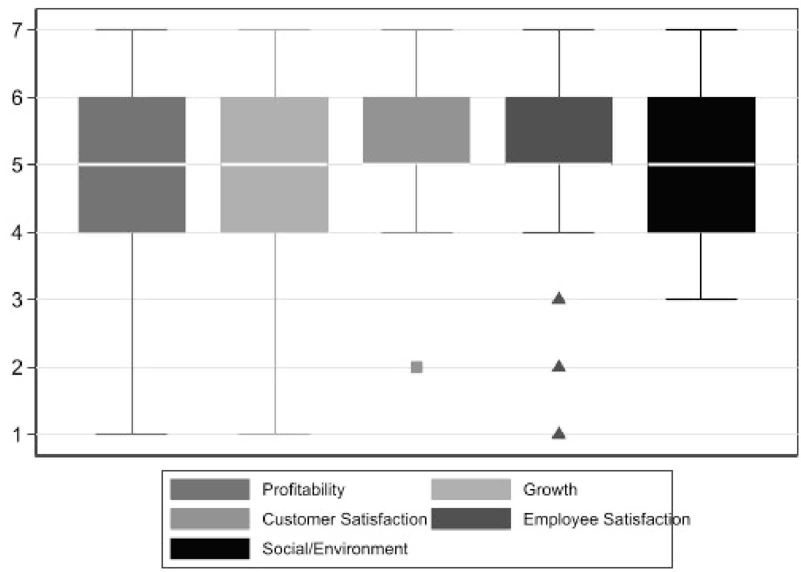

Figure 2 Distribution of the five performance measures

Relationship between Maturity and Performance

Given the similarity of the scores on the 12 items and the, yet, small number of responses, for the moment we assume – without statistical checking - that the items form a unidimensional scale of maturity. The overall maturity score is computed as the average score on the 12 items.

In later stages, we will compute separate scores for organization, skills, and infrastructure, and use these in the analyses, and look for 'better' groupings of the items.

The relationship between maturity and performance is likely to apply both ways. Assuming, for the time being, that the effect of maturity on performance is dominant, we have used a simple regression of performance on maturity. The results suggest that maturity has a statistically significant effect, of moderate size, on performance. Variation in maturity, accounts for 22 procent of the variation in performance. This positive relationship is depicted in figure 3.

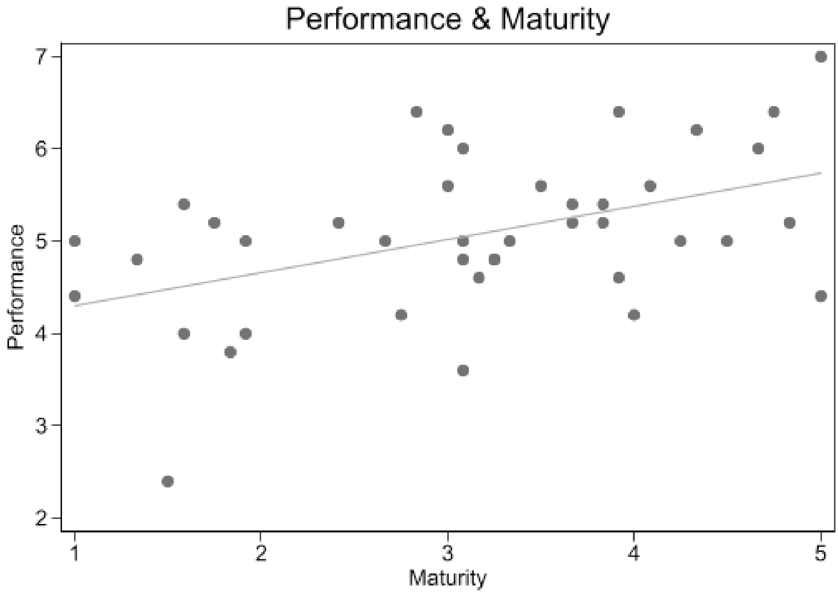

Figure 3 Relationship between maturity level and performance

Additional Questions

An additional set of questions has been added on challenges, bottlenecks, and strategic importance of data analytics. The results are shown in the table below. The results reflect the proportion of respondents who (strongly) agree with the statements, on a 5-point scale (from 1=strongly disagree, to 5=strongly agree).

Table 3 Results additional questions

	procent
Essential for survival	83
Aware of the possibilities	76
Jobs demand more and more digital skills	64
We know how we can work smarter	60
Growing need for analytical specialists	57
Permanent agenda item	55
Projects prioritized	55
Preparing for a digital transition	48
High investments are a bottleneck	43
We experience resistance	31

The results presented in table 3 indicate that a large share of the involved companies strongly agreed with the statement that data analytics is essential for business survival. Furthermore, they indicate that they are aware of the possibilities in terms of value creation. The results also show a growing need for more digital skills and therefore analytical specialists.

Conclusion and discussion

In this paper, we propose a user-friendly Maturity Model which can be used (1) for gaining insight into the current state of practice regarding the analytics maturity of companies and (2) to analyze the statistical relationship between the level of maturity and organizational performance. The proposed model is based on two existing and widely used Analytics Maturity Models: The INFORMS Analytics Maturity Model (IAMM) and the TDWI Analytics Maturity Model. We decided to use the structure of the IAMM (three blocks of four items each) and the answering scale of the TDWI model.

In addition, we present the results of our preliminary-study which provides a tentative understanding of the Analytics Maturity of SMEs in the logistics sector in the province of Gelderland. Although the small sample size (N=40) of this preliminary study does not allow any definitive conclusion, the first results reveal that maturity has a statistically significant effect, of moderate size, on performance. Variation in maturity, accounts for 22 procent of the variation in performance.

The results of an additional set of statement questions reveals that a large share of the involved companies consider data analytics as essential for their survival and are aware of the possibilities in terms of value creation. In addition, they indicate that there is a growing need for more digital skills and therefore analytical specialists.

When it comes to future research, the preliminary study presented in this paper can be regarded as starting point for a further rollout. The aim is to increase the current sample size of 40 companies to at least 200 SMEs in the logistics industry. That way we get a deeper understanding of the current domain situation and possibilities for improvement. Moreover, the research will make use of a panel design. One of the advantages of a panel design is the ability to determine causes and effects, rather than correlations. Furthermore, triangulation using in-depth qualitative studies will be used to fully understand how maturity and organizational performance interrelate.

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