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Measuring the Maturity of the Business Intelligence and Analytics Initiative of a Large Norwegian University:
The BEVISST Case Study

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ABSTRACT

Maturity models of business intelligence and analytics (BIA) have been previously used to assess BIA development progress in organizations in many sectors, such as healthcare and business. However, there is a lack of studies reporting up-to-date knowledge on applying maturity assessment in higher education institutions (HEI). It remains unclear precisely to what extent and how HEI employ maturity assessment and the benefits of such exercises. This paper addresses this gap by reporting a case study at a large Norwegian university. A domain-specific maturity model is used as a lens to observe and reflect on the BIA implementation at the Norwegian University of Science and Technology. This paper reports the assessment results and discusses the implications of the maturity assessment. The findings and discussions in the case can cater to a broader audience of BIA practitioners and researchers, contributing to understanding the value and adoption dynamics of BIA in higher education.

KEYWORDS

Analytics, Business Intelligence, Case Study, Higher Education, Maturity Model

INTRODUCTION

Technology advances in data availability and processing have made it increasingly possible to base decisions on quantitative evidence. With the ever-increasing focus on digitalization and data-driven or data-informed decision making, there is growing evidence of the importance of Business Intelligence and Analytics (BIA) for organizations. Business Intelligence (BI) has a rich history with origins from early decision support systems (DSS). Various definitions of BI have been proposed, each with emphasis on different capabilities of BI, such as executive information systems, expert systems, and online analytical processing. Wixom and Watson (2010, p14) describe BI as *"a broad category of technologies, applications, and processes for gathering, storing, accessing, and analyzing data to help its users make better decisions."* With the arrival of Big Data, analytics has increasingly been used to describe the more predictive and diagnostic applications that provide decision support (Davenport & Harris, 2017; Hardoon & Shmueli, 2013; Beyer & Douglas, 2012). In this work, the authors adopt a broad, inclusive and inspirational definition and denote the term BIA to *technologies, applications,*

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and processes for gathering, storing, accessing, visualizing, and analyzing data that enable enhanced insight, better decision making, and process automation.

It is currently ever more relevant to periodically assess the progress of BIA initiatives in delivering the expected value to business users. Although Higher Education Institutions (HEI) in Europe are seldom directly business-driven, such assessment is equally relevant, partly due to the perceived need to increase public investment efficiency in Higher Education (HE) as an economic good (De Wit & Broucker, 2017). On top of the economic rationale, there is also an internal drive to compete for qualified students and the best faculty who excel in the teaching programs and research projects. HEI, like other organizations, are trying to become more data-driven and make data-driven informed decisions to improve their effectiveness (Drake & Walz, 2018). In this setting, the alignment between information systems and business needs is vital to ensure the delivery of HE's public value and stand out from competing HEI. Business intelligence and analytics have been instrumental for many years in delivering this alignment. For example, BI has been applied in HEI to ensure compliance (Niño et al., 2020) and understand student learning characteristics (Kabakchieva, 2015).

It is well acknowledged that organizations that successfully deploy BIA systems follow an iterative path, starting with a rudimentary usage of data and analytical tools, and progressing to a growing sophistication of their BIA applications until the BIA data-driven culture becomes embedded in the organization's activities and decision making. The design of maturity models tries to map this progressive path, in which an organization starts with a basic or initial stage of maturity and progresses towards a more mature state. Maturity is therefore related to this notion of evolution or progression. Maturity models (MM) play an important role by reducing the uncertainty of how BIA managers perceive the BIA systems' maturity in their organizations. Some existing MM enable the possibility to benchmark one's BIA systems' performance against the average performance of other organizations in the same industry. Furthermore, MM establishes an evolution path that, with a set of recommendations, helps organizations know what to do next to achieve a higher level of maturity.

This paper presents the BEVISST case study, a BIA project implemented at the Norwegian University of Science and Technology (NTNU), in Norway. A domain-specific maturity model is used as a lens to observe and reflect on the BIA project. The findings and discussions of this case can contribute to a wider understanding of the value and adoption dynamics of BIA in HE.

The rest of the paper is organized as follows. The knowledge gap leading up to the research question is first elaborated in Background. We then introduce the HE-BIA MM and describe the case settings. In the Result section, we present the result of the MM assessment and shed light on the usefulness of the MM. We proceed to relate the findings of this study back to the prior work of others in Discussion and conclude the paper after that in the Conclusion section.

BACKGROUND

Several BIA MM are reported in the literature (Sen, Sinha & Ramamurthy, 2006; Raber, Winter & Wortmann, 2012; TDWI Research 2012; OCU 2013; Cosic, Shanks & Maynard, 2015; Spruit & Sacu, 2015; Halper 2018, Davenport 2018). Many of these models focus on a specific set of processes, such as project management or learning management. Often, they are not directed towards any particular application or business domain. This approach allows the same maturity model to be used across different industries. However, such an approach tends to be complex, with many assessment questions and a terminology set that does not significantly overlap with the vocabulary and definitions in a particular domain. Past survey experience in HE shows that such complexity and discrepancy resulted in difficulties in assessing BI solutions' maturity correctly (Cardoso et al., 2013). The lack of understanding of critical concepts and complications in locating the expert(s) who has the capabilities of in-depth knowledge of many diverse questions were among the main reasons reported in the study.

HE is a closed domain in the sense that HE managers, especially in Europe, tend to avert from business-oriented terminology. The controversial debate on students as customers is a typical example.

While the student-as-customer metaphor might be appealing to some, its implications are contested by others (Harvey & Green, 1993; Houston 2007). Education is not a transaction, but rather an ongoing transformational process dependent on the students' willingness to participate in learning (Beaver, 1994). Students could be viewed as customers because they pay for the service. Paying tuitions, however, all but entitles the student to a desired grade or degree. Although students pay a proportion of the HE costs in tuition fees, HE is still mainly funded by the government and through taxes. Therefore, students are neither the only consumers in HE nor necessarily the most important customers. This kind of discussion often surfaces when trying to apply business-driven approaches to HE. A domain-specific maturity model, using the vocabulary understood by the HE community, might enable a more focused and fruitful maturity assessment exercise.

The BIA field is going through rapid changes, with a shift from heavy Data Warehouse focus to increasing emphasis on issues such as Big Data, Internet of Things (IoT), and Natural Language Processing. Such changes are not sufficiently captured and reflected in many of the existent MM in the literature. Apart from domain-specific, the goal was to use a MM that could capture the recent development of advanced analytics. To this end, we designed and implemented a lean and domain-specific BIA MM for HE (Cardoso & Su, 2019; 2020).

MM has been previously used to gauge and assess BIA projects in healthcare with domain-specific models (Gastaldi et al., 2018; Brooks, El-Gayar & Sarnikar, 2015). The OCU model (2013), a domain-specific MM for HE, has been used mainly in the United States. However, the model has not been updated and therefore does not capture the new development of the BIA field. In (Ülker & Coskun, 2021), the authors reported how different types of analytics were used in 12 Turkish universities and mapped the sector in Turkey as a whole roughly at the analytically impaired level of the analytical MM of Davenport and Harris (Davenport, 2007). There is a lack of studies reporting up-to-date knowledge on applying maturity assessment in HE. It remains unclear precisely to what extent and how HEI employ maturity assessment and the benefits of such exercises. This paper addresses this gap by reporting a case study at a large Norwegian university, using a domain-specific MM as a lens to observe and reflect on the BIA implementation at the Norwegian University of Science and Technology (NTNU). Central to the case is the BEVISST program at NTNU.

In this paper, we explore the following research question: *"To what extent and in what way is it useful to perform a maturity assessment of BIA in a HEI?"* Therefore, we explore how a maturity assessment in HEI can be carried out with the assistant of a domain-specific MM and precisely how it is useful to the BIA team, individually, team-wise, and organizational-wide.

THE MATURITY MODEL AND CASE SETTINGS

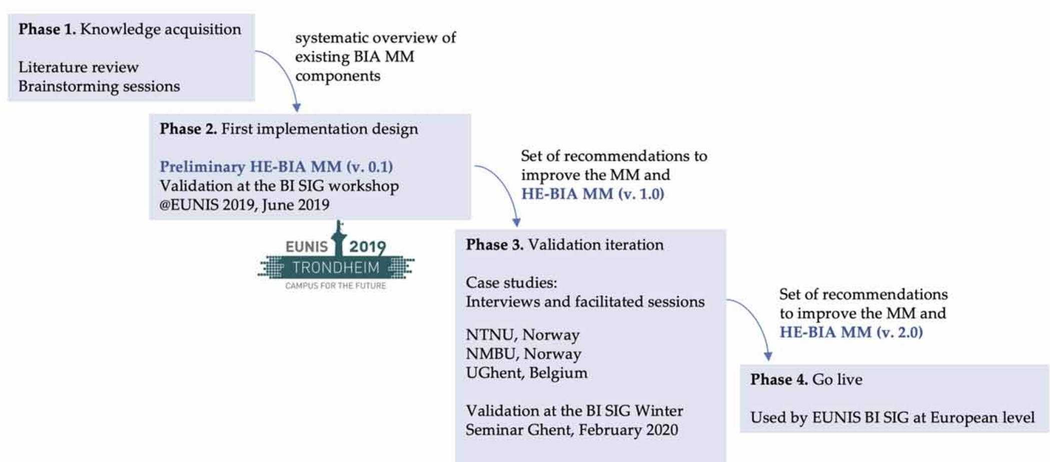
The HE-BIA Maturity Model

In this study we choose to use a new maturity model, designed specifically for Business Intelligence and Analytics developed in HE. The model was developed according to the research setting displayed in Figure 1. This model results from iterative design science research (Peffeers et al., 2007-8). It was started with a systematic overview of existing BIA MM components (Phase 1), followed by the first implementation design originating Version 0.1 of the model (Phase 2) (Cardoso & Su, 2019). This version was discussed and validated at the BI SIG workshop at the EUNIS congress in June 2019, in Norway, by roughly 30 BI practitioners in HE in Europe. The BI SIG is the Business Intelligence Special Interest Group of EUNIS, the European University Information Systems, a non-profit organization that aims to foster the collaboration and sharing of experiences among European HEI. In the workshop, the usefulness of the MM was positively confirmed by the practitioners. The practitioners reported that:

- *It helps to focus on the right things*

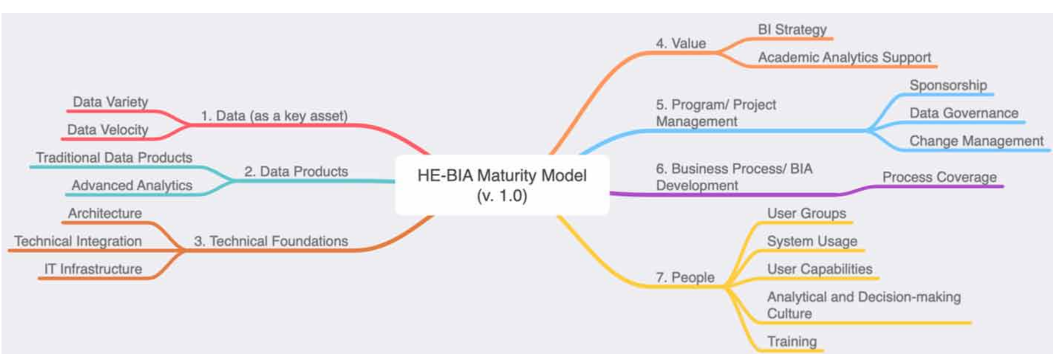
- *Useful for making management more aware of the need to invest in BI*
- *Great help for discussion (such that one does not forget important aspects)*
- *Useful as a reference maturity model*
- *Great tool for benchmarking. Will help HEI to implement BIA strategically and to plan activities*

Figure 1. The HE-BIA maturity model research design



A set of recommendations to improve the MM was also solicited during the workshop and systematically analyzed, grouped, and incorporated into an improved version of HE-BIA MM (v. 1.0). In Phase 3, the model was tested in three case studies (different institutions) and another BI SIG workshop, that took place in February 2020 in Belgium. This paper reports the in-depth findings of one case study, at the Norwegian University of Science and Technology, in Norway. Version 1.0 of the MM was applied in the current case study. The final version of the maturity model (v2.0), incorporating the feedback received during Phase 3, will be made available to the community of practice. The goal is to use this model as a tool to assess the maturity of BIA solutions at the European level, in the context of EUNIS BI SIG activities.

Figure 2. A high-level overview of the HE-BIA maturity model



The model is designed with two parts: Technology and Organization. The technology part is depicted on the left side of Figure 2 and consists of seven technical dimensions. The organization part, on the right side of Figure 2, consists of 11 dimensions. Dimensions are grouped into categories. The HE-BIA MM is structured with seven maturity categories: Data (as a key asset), Data Products, Technical Foundations, Value, Program/Project Management, Business Process/BIA Development, and People, as displayed in Figure 2 (named 1 to 7).

Each dimension is described with five maturity levels: Pre-adoption, Initial stage, Managed stage, Systematic and Optimized. An example of how the dimensions and levels are organized is shown in Figure 3. The complete description of the MM can be found in the Appendix, in Figures 7 to 9.

Figure 3. HE-BIA maturity model (v. 1.0): example of dimensions and levels

Data Products	**Traditional Data Products**	**Advanced Analytics**
Dimension definition	Development and utilisation of reports, dashboards, scorecards, OLAP (online analytical processing) and data visualisation technologies to display output information in a format readily understood by its users, e.g., managers and other key decision-makers.	Development and utilisation of sophisticated statistical and data mining/machine learning software to explore data and identify useful correlations, patterns and trends and extrapolate them to predict what is likely to occur in the future.
Level 1: Pre-adoption	Only static and parameter-driven reports are available.	Currently not applicable.
Level 2: Initial	Business intelligence tools are in place for enterprise reporting. Ad-hoc reporting and OLAP are supported.	Limited ability for statistical modeling, typically performed one-off.
Level 3: Managed	Enterprise-wide definitions are in place for key business metrics. Power users create data mashups from multiple sources.	Limited use of predictive and statistical modeling capabilities mostly through manual calculation and forecasting. Basic batch predictive models have begun to emerge.
Level 4: Systematic	Organizations have broad user access to BI using embedded dashboards within key applications and mobile BI. Users can perform ad hoc analyses and visualizations. Well-defined data dictionaries and data governance policies are established.	Predictive models have been developed for multiple purposes such as student retention analysis and predictive maintenance for equipment. Organizations begin to develop prescriptive models that generate recommended actions for users based on analysis of data.
Level 5: Optimized	Organizations have established interactive and streaming BI dashboards for enterprise-wide KPIs. Business users are enabled to use BI tools to customize their view of the state of business and identify opportunities and risks through user-defined, custom alerts.	Predictive models are based on real-time data streams and update dynamically (e.g., real-time campus space occupancy). Models are deployed within key business applications to support real-time operational decision making and personalized recommendations. Data scientists have the ability to build, refine, and select the best model after having run multiple in parallel.

Case Settings

NTNU is the largest university in Norway today, with a history dating back to 1910. NTNU is headquartered in Trondheim, with campuses in Gjøvik and Ålesund. It has eight faculties, as well as the University Museum and University Library. As of 2019, the university has 42 000 students and 7400 full-time equivalent staff, with the main profile in science and technology, as well as other academic disciplines including humanities, social sciences, economics, medicine, health sciences, educational science, architecture, entrepreneurship, art disciplines, and artistic activities. It offers 371 study programs with 394 doctoral degrees and 7586 bachelor and master degrees awarded in 2019. The university is also the host or partner for 35 large research centers and a budget of 9,4 billion Norwegian Kroner.

BEVISST is the BI system at NTNU that helps managers gain access to management and management information in their institute and faculty (and compare their units with other units at NTNU, if desired). BEVISST is in short for Bedre virksomhetsstyring (Better Governance), and the word “bevisst” means “conscious” in Norwegian.

The BEVISST system provides, among other things, standardized key figures for an institute or faculty and NTNU in general. Therefore, it renders possible comparing key figures across units and within the same unit (e.g., overtime or on given parameters). It is also a support tool in business processes, where managers and management support can gain better insight into core areas such as education, finance, human resources (HR), and research.

The BEVISST BI system is the result of a strategic project with the same name. The BEVISST project started in 2010 with the original aim of acquiring and implementing an IT system that would facilitate the work on corporate governance at NTNU, especially in the planning and budgeting processes. The planning and budgeting processes at Norwegian University (called PBO process in Norwegian, that stands for Plan-, Budsjett- og Oppfølgingsprosessen) are both complex and important for two reasons. Firstly, the processes need good quality data from many different sources. Secondly, they go through all three levels of the university (departments, faculty, and central) and are the bases for resource allocation at these levels. The project had a halt in 2013 when the original solution (integration directly from source data with no centralized data warehouse) lacked flexibility and failed to deliver the expected results.

In 2014, the project restarted with the acquisition and implementation of a data warehouse and an extended scope, supporting more than just the planning and budgeting process. In January 2015, the board of NTNU decided to merge with the University Colleges of Sør-Trøndelag, Ålesund, and Gjøvik to form a new university. The merger, which went into effect in January 2016, made NTNU Norway’s largest single university. As a result, in the fall of 2015, the project was further delayed and extended to best accommodate the changes incurred by the merger, where coordination and integration of data, systems, and processes from different sites became necessary.

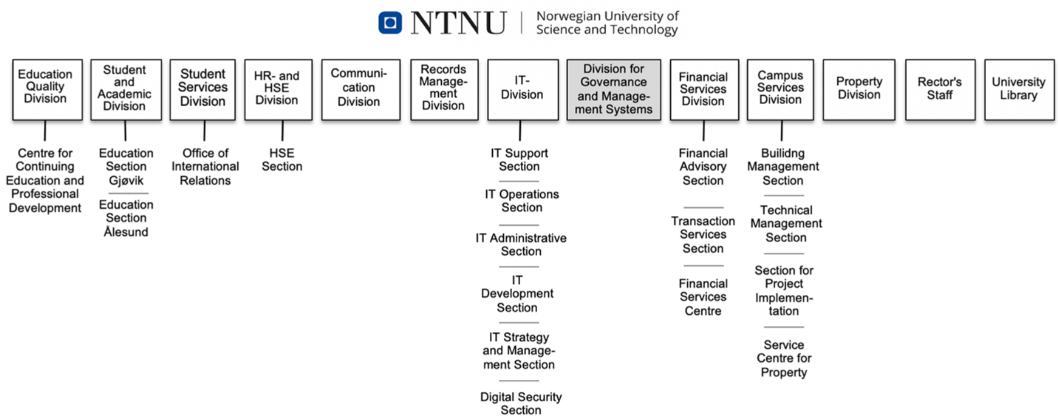
This project ended in 2017; a unit was established in the line organization to take over the daily operation, deliver BEVISST BI as a digital service, and plan and roll out the BI system’s further development. Over time, the BEVISST digital service expanded its product portfolio, including: (1) BEVISST Plan that supports the aforementioned PBO process and (2) BEVISST INNSIKT that provides management access and analysis to core data in HR, finance, education, and research. BEVISST is primarily designed for management but is also available to management support staff. As of the start of 2020, the system has around 120 super users who can design their own reports and share with others, and approximately 1350 consumer users who read reports daily, weekly and monthly (Kibsgaard, 2018).

The team, BEVISST BI, is under the department of Governance and Management Systems as part of the central administration at NTNU (see Figure 4). The BI team at large consists of three teams coordinated by one BI manager:

- A scrum team of six developers and operational staff;
- A team for the report solution with eight product owners for the different reports, one educational analyst and one test leader;
- A team for the planning solution with seven product developers (business architects), one information architect, and one solution architect.

The authors got into contact with the BEVISST team through common engagement at the EUNIS BI SIG. The team lead (BI manager) facilitated the case study and access to data and key persons. The data collection was carried out primarily on-site at NTNU in periods when both authors were physically present.

Figure 4. Management and administration structure of NTNU (NTNU, 2019)



Data and Data Analysis

Two facilitated sessions (FS), of two hours, were conducted on-site with the BEVISST team members in October 2019. The first FS targeted product owners and user representatives and had five participants. The second FS, with four participants, included members of the technical team. The team lead was present in both sessions but participated as an active participant only in the first FS. Each FS participant received a printed version of the MM, a brochure explaining how to do the assessment and a feedback form. Both FS followed a similar procedure, as shown below.

1. The facilitator (one of the authors of this paper) introduces the maturity model and the workshop's plans (10 min).
2. Each participant reads the assessment materials (How to do the assessment brochure and the MM (10 min).
3. Divide the participants into groups of 2-3. The local assessment sponsor should take into account group dynamics.
4. Each group does the assessment independently, scoring each dimension of the model (using the printed version of the MM) (30 min).
5. The facilitator leads the discussion to reach consensus about the final score of each maturity dimension and presents a visualization of the results (1h).
6. Participants write the feedback form (10 min).

An Excel spreadsheet was used to support the facilitator in the discussion part, to collect the scores from the different groups, and the consensus score for each dimension. This enabled the facilitator to immediately present a visualization of the results, using a radar chart (as the one displayed in Figure 5).

Two semi-structured interviews were carried out in days after the FS. Interview 1 was directed towards the BI team's key sponsor, and Interview 2 was directed towards the team lead (i.e., the BI manager). Both interviews lasted about 1 hour. Apart from the aforementioned primary data sources, document analysis was also carried out on the archival documents produced by the BEVISST project. Table 1 presents a summary of the research engagement in terms of the collected data in this study. The primary sources for analysis were data obtained from the measurement model, facilitated sessions and interviews. Document analysis, such as the final project reports and the reports on proposed governing structures to organize BEVISST as a service, provided rich context information to understand the BIA journey at NTNU. To a limited extent, the document analysis was also used to triangulate results from the primary sources.

Table 1. Data types, temporal extent, and themes covered in the case study

Data Types	Sources	Theme
Participatory observations; Discussion in the facilitated sessions	Results of the MM assessment, observation notes, user feedback, and discussion at the FS in the form of notes written down during both FS (4h)	A firsthand impression of how the MM is used in a team setting
Direct (written) feedback from the two FS participants	Four feedback forms filled out by the participants	The usefulness and adequacy of the MM as well as specific feedback on dimensions
Interview 1 with key sponsor	Interview recorded and transcribed (1h)	Understand the BI initiative's context and possible roadmap, probe the connection between MM and road map
Interview 2 with the team lead	Interview recorded and transcribed (1h)	Capture the reflections on the MM and the assessment process
Document analysis	Archival documents produced by the BEVISST project/team	Understand how BI evolved in the last ten years at NTNU and to a limited extent help to triangulate the results from facilitated sessions and interviews.
Software analysis	Access to the BEVISST platform	A firsthand impression of the functionality of the BI platform

The data analysis in this case study was guided by Clarke and Braun's principles and steps for interpretive research (Clarke & Braun, 2016). Prominent themes in the data were found through a six-step analysis process. The coding was performed iteratively through a data-driven process where relevant excerpts were listed and grouped (using the Nvivo software). Emerging themes were then identified and used to cluster excerpts. Recoding and regrouping were performed until stable prominent themes were identified.

RESULTS

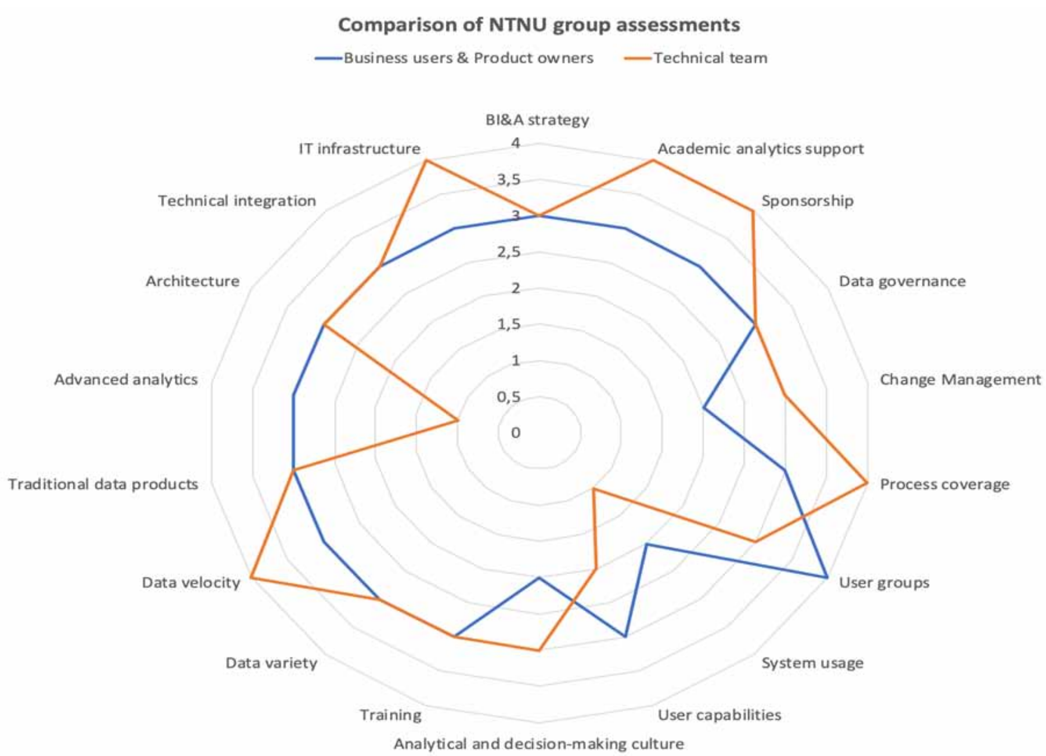
Analysis of the data revealed a set of themes regarding the usefulness and adequacy of the maturity model. The results of the MM assessment will be introduced first. This step is necessary because it explains how the usefulness of the MM starts to emerge.

Maturity Assessment Result

The two facilitated sessions resulted in two assessment results: product owners and user representatives and another from the technical development team. Each group achieved consensus internally at their respective FS. Between the two groups, there are apparent discrepancies, as shown in Figure 5.

The technical team scored higher on the maturity scale for the seven technical dimensions than their business counterparts, except for Advanced analytics. It seems that the business users reported that they are having some sporadic pilot studies of predictive models. At the same time, the technical team either was not aware of it or did not seem to reckon that these attempts are seriously qualified as Advanced analytics. The technical team had good confidence in the technical infrastructure and believed they "can" easily scale up to increase refreshing rate and capacity.

Figure 5. MM assessment results

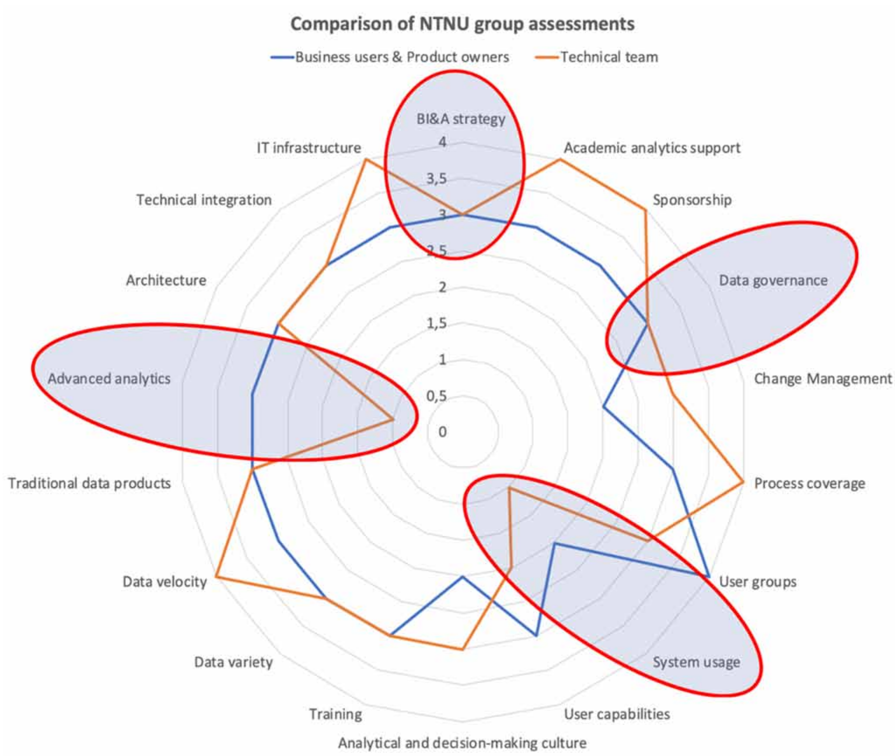


For the 11 organizational dimensions, the technical group scored lower in three dimensions: User groups, System usage, and User capabilities. If overlaying this figure with the categories in Figure 2, it becomes apparent that all these three dimensions are in the People category. The technical team's recurring theme seems to be "the platform is capable and flexible with many potentials, and the users need to engage with the platform deeper and wider." For the business group, their score has a drop in three dimensions: System usage, Change management, and Analytical and decision-making culture. In fact, the Analytical and decision-making culture is one of the dimensions that drew a fair amount of discussions at both sessions.

After presenting the results to the team, some dimensions drew particular attention. These are BIA strategy, Data governance, System usage, and Advanced analytics, highlighted in Figure 6.

The BIA strategy dimension relates to defining and managing the BIA solution's vision and strategy and how it supports the university's strategy. A previous study also indicated that not having an effective business intelligence strategy is a significant issue with regard to trying to realize organizational benefits (Hawking & Sellitto, 2015). Such a BIA strategy is essential to ensure close alignment of BIA outcomes with the organization's needs. At NTNU, the team agreed that the BIA plan is defined at the university level and is aligned with the plan of different faculties and departments of the university. The team reflected on this strategy's importance, such as its vital role in management buy-in and resource prioritization. However, much work is still needed to complete the full strategic loop: from planning, executing, monitoring, and improvement of the BIA strategy.

Figure 6. NTNU BIA maturity assessment: dimensions that drew particular attention



Data governance measures the level of adherence to data governance practices and methodologies. Data governance covers considerable territory: from deciding who owns and can access data to developing metadata to choosing appropriate data sources (Halper, 2014). For example, a university might use socioeconomic and learning participation data to predict future student retention rates. However, if the different units have not agreed on which socioeconomic data or learning participation data to use, results can vary between departments. Here both teams agreed that they are at level 3 where initial policies and methodologies for data management start to be defined. The teams, especially the technical team, were aware of the need for better quality control, and the need to appoint possibly a data steward, to drive the organizational agreement on definitions, business rules, and to solve possible data conflicts between BIA projects. This MM exercise made the awareness of this need even more acute.

System usage measures the BIA solution's effective usage, determining the number of active users, considering the different user groups. Both teams were somewhat critical to the current situation of systems usage, where a large number of users at NTNU do not actively engage with the platform. However, it was argued that the nature of the university calendar (such as quarterly and biannual reporting) and pace made it unnecessary for some users to access the system frequently. Both teams keenly agreed that increasing system usage is vital, without which the value of the BIA system cannot be fully realized. It was not entirely clear how to achieve this. Some initial discussion points to the direction of a more intuitive interface and more training. It was also argued that the BIA solution needs to be part of the business process of users.

Advanced analytics is one dimension that aroused heated discussions. It measures the development and utilization of sophisticated statistical and data mining/machine learning software to explore data and identify useful correlations, patterns, and trends and extrapolate them to predict what is likely to occur in the future. Although traditional data products like reporting still take by far the largest share of BIA services, it is undoubtedly in advance analytics where much of the aspiration lies. The technical team is particularly keen to point out the university's vast potential in this area. In contrast, the business team is more concerned with real business cases where advanced analytics adds value in the HE sector.

Usefulness of Measuring Maturity of BIA in HE

The central research question in this MM exercise is to understand if and how an MM can be useful to a HEI. The main themes that arose from the data material are presented in this section. Relevant excerpts are listed to illustrate and give detail to the findings.

Ground for Common Understanding

It was quickly noticed that conversation and discussion happened naturally because the participants need to score the model first in smaller groups (2-3 people). Then, they need to reach a consensus jointly in each FS, and finally, the spider web chart exhibited the commonalities and differences between the two FS. This exercise helped them turn the mirror inward to bring their internal pictures of the BIA landscape at the institution to the surface. The differences triggered the participants to carry on "learningful" conversations that balanced inquiry and advocacy. This way, people were able to expose their own thinking effectively and make that thinking open to others' influence (Senge, 2006). As one participant reflected:

So, for me, the way I see it is that using this assessment exercise is a great way of actually constructing a joint mental model for the team of the situation and where we are different and where we do look differently upon things.

It was also suggested that for such "learningful" conversations to happen, some level of ambiguity in the model was a necessary element, as explained in the following statement:

They [the levels] are useful as they are described, no need for super crisp clarity here. It is a good basis for discussion, and that gives us the most value.

It also seems to be rather natural to discuss "as-is" and "to-be" situations in such an exercise, because the MM indicates a possible evolution path. It can be argued that the common understanding, in this case, includes both the current situation and possibly also the pictures of the future. The following observation gives us an example: Participant A and B scored the dimension Academic analytics between 2 and 3 but pointed to level 4 and added, *"of course, this is where we want to be."*

One relevant element in reaching a common understanding is raising awareness. During the workshop, it became clear that not all team members were equally updated on the different aspects of how the BIA platform works. This in part can be attributed to the fact that the team is highly cross functional with team members specializing in rather diverse areas such as ETL (Extract, Transform and Load) and data warehouse, information architecture, product owners and end user representatives (Kibsgaard, 2018). One rather direct outcome of the workshop is for the technical team to be more aware of how the products they are offering are actually being used in the organization and vice versa for the user representatives to be more aware of the fundamentals, challenges, and potentials of the underlying technical platform. Such awareness is a necessary first step to the alignment of the technical solution and business needs. Two participants reported the following statements separately:

I think the maturity model is very useful in the Higher Education sector because it highlights the issues we need to work more on and to document how the BIA platform works.
It can be used to bring the team more aware, more together.

Team Learning and Reflection

Team learning is an important aspect of what makes organizations successful over time, especially in today's information-intensive era. The set-up of the FS was carefully planned to provide room and ground for team learning. One of the recurring themes in the data material is how the MM has made it possible for the team to reflect together without being personal, as summarized clearly in the following excerpt:

It's a great exercise to use for the team to reflect together without being personal. That is a very, very good part of this maturity assessment model. We can actually talk about BI. We can talk about the difficulties. We can talk about strengths that we have, and challenges without being accusative… because you cannot do that or because you did not prioritize to use your time like that…

It was suggested that such a depersonalized and team-oriented setup helped to turn off the automatic defense mechanisms when people feel that they are being criticized and evaluated. Instead, the team members considered:

It's evaluating how we are working with all these outputs and all these different dimensions. How are we on data? How are we on IT infrastructure? How are we on that? And it gives us all the opportunity to have an opinion about all of these things, and it also gives us an opportunity to discover the opinions of the others, which is a great value for a team.

Likewise, it also allows the individual to reflect on their position in the team without being personal. The team reported that levels are suitable to use as a basis of discussion and reflection upon where they stand (i.e., the current state of affairs). Here it was also suggested that some fuzziness could be a good element in this exercise because fuzziness naturally leads to discussion. The team also reported that they even deliberately problematized some of the dimensions to foster a good discussion. Ultimately, what the team considered of most value was the learning experience. When questioned about the usefulness of the maturity levels, one participant shared what was most important for them:

And the discussion and what we learn from it. So, it's not two or four or three, which is important. It's the discussion and the outcome, the personal outcome for everybody by themselves, and the ultimate outcome together as a group – the learning experience. That's how I see it.

Surprisingly, the team considered it more an exercise for team building than for benchmarking. For team building, participants also liked it that everyone came to the workshop without much preparation because:

…then you do the discovery together. You do the discussion of the definitions and the dimensions together, and you haven't made up your mind about anything before you come there, which is great. So, you do the discovery and the discussions together. It's what happens in the team while you were there that is of value, and the output of what you do together.

Benchmarking Potential

Although benchmarking was initially one of the MM's intended usages, it gradually became clear that the MM in its current form has more potential as a team learning and team-building endeavor. Even so, participants were genuinely interested in understanding where they are compared to peers. Such comparison would bear the best result if it is within the HEI sector, as explained by one participant:

For now, it's hard for the steering board to understand what we are doing when we talk about other teams and organizations that many times is not within our sector because we don't have that many BI teams in our sector. It's rather new, making it difficult to understand for some of the steering board members. And it would have been – I'd very much appreciate it if other universities outside our country are taking part in this because that would allow us to compare.

They were, in the meantime, keenly aware that a different set of criteria might apply when benchmarking is the focus:

If we're doing benchmarking with other institutions, it might not be so easy to compare ourselves because we take in different understandings of these dimensions. So, for the users, for us as an institution on our own, maybe it doesn't matter that much. However, for you, as researchers, it's interesting to see if you could use this as a measurement, and then it's more important that you have a stricter definition [of dimensions and levels] maybe.

It was also pointed out that in HEI, at least in the Norwegian context, sharing is more important than competing. In such a context, benchmarking is more an instrument to share and learn best practices and move the whole sector forward.

Strategizing

Strategizing is the process of devising a coherent course of action to make sure that the organization creates value for the long term. It is well-documented that one of the strategic challenges is the tension between short-term focus and goals and long-term focus and goals, the so called intertemporal strategic decisions (Siebelink et. al., 2021). In our study, strategizing turned out to be one of the last important themes that was repeatedly mentioned, as summarized in the following quote:

So, for me, this is a great - sorry to use the word - tool. It's a great tool for a team-building activity where you can strengthen a team and discuss about the everyday operations, but you could also discuss about strategies. How are we going to move forward with this?

The team leader considered using the MM result for management buy-in:

I will use the result to help them [the steering board] to get on board on where are the challenging issues. Of course, every time I meet the steering board, I present our risk metrics. And it's so easy for them to plunge into and be detail-oriented about the risk. And they think about, "Oh, you just need to fix that one thing, and we're fine. And it's green. Instead of thinking about it in a more structured way and an overall level scene, all these things combined, they actually are so integrated that you can keep on fixing a small patch over there or a small patch over there, but unless you think about it in a more structured way, you're not going to solve anything, really. And this is a great way of showing that picture.

Many participants also asked the natural question: what about road mapping? The MM result itself does not directly generate a roadmap. However, as indicated in the result section, some dimensions drew special attention to the team during this exercise. Such a list can be a good starting point for prioritization. To summarize, one argued that:

[The MM is] great to use for reflection and learning experience on how to proceed with a road map for future actions.

DISCUSSION

This study aimed to investigate to what extent and how it is useful to perform a maturity assessment of BIA in a HEI? The case study showed that applying a domain-specific MM assessment can present the team with a holistic view of their BIA program's development stages. For many, it is refreshing to be exposed to a structured and overall level BIA scene. It helps them to realize how integrated and intertwined the different aspects of BIA are. The awareness of the development stage is considered useful by the participants. This is in line with other studies that have reported MM's popularity with practitioners because of their perceived usefulness (Wixom & Watson, 2010; Eckerson, 2007). In the meantime, the discussion of the current stage also forms natural gravitation towards dimensions that the team instinctively considered essential to move forward in the future. Although one may argue that it is beneficial to move the levels across all dimensions at a similar speed, it is, in practice, difficult to move all dimensions in synch. Other researchers have repeatedly pointed out the lack of comprehensive models to help practitioners with the priorities that should be followed to develop a proper BI solution (Pfeffer & Sutton, 1999; Chen et al., 2012; Gastaldi et al., 2018). In this work, hints and cues on where the group focuses its attention (as presented in Figure 6) may serve as a good starting point to distinguish and prioritize the aspects that require immediate attention (e.g., what to move next).

Organizational Learning and Reflection

The study reveals the usefulness of the MM as a team learning and reflection instrument. Several aspects of this finding warrant discussion. In the study, it was noticed that when discrepancy happens while participants are scoring the model, it gives an opportunity to convert the situation into one where both parties can learn. This requires a combination of articulating one's views and learning more about the other side's views—a process that Argyris calls "balancing inquiry and advocacy" (Argyris & Schön, 1996). When appropriately used, as is the case here, the MM assessment facilitates dialogue and allows the teams to form a common understanding of the current and possible future situation of their BIA program, both technically and organizationally. By forming a common understanding, they create a common image as a basis for reflection, learning, and, consequently, a shared knowledge base for future directions.

Previous studies have described the importance of establishing learning as a regular practice through reflection and exploration of each other's mental models (Senge 2006; Lui, 2020). The MM assessment contributes to "objectify" the conversation. The conversation is then about "the structure", the systemic forces at play, not about personalities and abilities. Challenging questions can be asked and discussed in a way that does not carry the implication of incompetence or implied criticism.

Knowledge Sharing

A large amount of information was externalized during the assessment process. Some of these, such as how many users does the BIA platform has, is relatively factual. Other such as the process of how a change request to the BIA platform is registered and resolved, is more tacit. When faced with the decision on which are the correct scores at all these dimensions first pairwise, then at a group level, the participants are both allowed and forced to elaborate their understanding and externalize their assumptions and reasoning. They started to ask each other questions about definitions, products, processes, use cases, etc. Sharing implicit knowledge between actors is considered a socialization process (Kakabadse et al., 2001; Inkpen, 1996). During such socialization and interactions, externalization and knowledge transfer happens as individuals share know-how with each other and within the group. It starts with the information making its way to the team's collective awareness and proceeds as teams discuss and debate this information until it becomes part of their collective knowledge state (Wiese & Shawn, 2019). It is argued that for knowledge sharing to happen, it requires, among other things, environments that provide extensive opportunities for communication and experimentation (Senge, 2006; Davenport & Prusak, 1997). The MM assessment session can be considered one of such environments.

Change Engineering

Ultimately, the purpose of MM is also to identify a gap between the actual and the intended organizational design, which can then be closed by succeeding development activities (Pfeffer & Sutton, 1999). However, many of the MM do not describe how to effectively perform these actions, or even which actions to perform first. This "knowing-doing" gap can be very difficult to close. In the organizational context, closing such a "knowing-doing" gap calls for carefully crafted change engineering. The term "change" can be understood as an alteration in the people, structure, or technology. (Woodman, 1990) argues that effective change engineering largely depends on a valid identification and exploration of what the organization does well or poorly. Argyris pointed out that effective change engineering is based on valid and useful information about the organization and its problems, free and informed choices, and an internal commitment by the involved people to carry out the intended actions (Argyris & Schön, 1996). From this case study, it was observed that the HE-BIA maturity model functioning as a facilitating instrument for decision-makers and change-agents to analyze the state of an organization in order to be able to initiate appropriate actions.

There is no immediate evidence to support that a measurable change has happened due to the MM engagement. However, the team does report afterwards that they find the MM exercise of great value as a learning exercise for the team, and they intend to repeat it in order to improve how they work together and also to make better decisions on how to proceed with their work. This continuous engagement with the MM is in many ways an enabling factor for an effective roadmap for change. Through road mapping, an organization can review its product directions, technology timing and recognize how to create the right products at the right time to improve short-term and long-term prospects of the organization (Siebelink et. al., 2021). In this context, the factors mentioned above, namely, organizational learning and reflection, and knowledge sharing as a socialization process, are considered important prerequisites for effective change engineering.

Recommendations

Finally, for HEIs that are aiming at improving its BIA maturity with the help of MM, the following recommendations are of relevance.

1. As much as benchmarking is important to assess the current state, equally important is to bring the team to the same mental picture.
2. To achieve fruitful organizational learning and reflection for a BIA team, the MM needs to be sufficiently high level, at the right level of complexity, and inspirational.
3. Domain knowledge and domain specific terms and examples can improve the precision of the assessment as they are more relatable and recognizable by the members.
4. The MM is both a product and a process. How to run the assessment process is of equal importance as to which model to use.
5. Recognizing that it is a journey and use the MM to kick start the road mapping process.

CONCLUSION

BIA systems are becoming increasingly critical to the daily operations of HEI. For knowledge institutions like universities, it is critical to empower management in the institution with information that allows them to make decisions based on a solid foundation of facts. However, just acquiring and implementing Data Warehouse and BIA systems seldom lead to success by itself. BIA systems share similar characteristics with other infrastructural projects, such as enterprise resource planning (ERP) systems implementation. That is, implementing a BIA system is not a simple activity entailing merely the purchase of a combination of software and hardware; rather, it is a complex undertaking requiring appropriate infrastructure and resources over a lengthy period (Yeoh & Koronios, 2010). Therefore, the notion of "maturity" can be instrumental in such a lengthy period, enabling BIA systems to follow an iterative path, from less maturity to full development. Various maturity models have been proposed to depict such an evolutionary path, most of which emphasize the importance of paying attention to both technical and organizational BI capabilities (Işik et al., 2013).

This study was carried out against the backdrop of these MM and their applications. This paper reported a case where a domain-specific MM was used in one HEI. In this study, other than using a generic model such as DELTA Plus model (Davenport, 2018) or the TDWI MM (TDWI Research 2012), the authors opted to use a model with HE domain-specific terminology. For instance, instead of using more general terms such as "core business and support functions," the authors used "Research, Education, HR, and Finance" which are more anchored and easily recognizable in HEI. The level descriptions were also supplemented with appropriate examples in HEI. This brings clarity in the process and makes the assessment easier to relate to for the participants. The authors investigated how the HE-BIA maturity model can be used in a HEI and how it is useful to the BI team, individually and team-wise. This research contributes to the body of knowledge on maturity assessment both as a product and a process. On a more practical level, it can be envisaged the HE-BIA model being used as a self-assessment tool in other HEI. It would be interesting to see if other HEI can benefit from such an exercise in a similar fashion. The authors have described the maturity assessment process in lengthy detail, hoping that any attempts to replicate the process are attainable.

During the case study, feedbacks and comments on further improvement of the MM were solicited and systemized. Work on revising and updating the MM is well underway. This work centers around a single case and bears the limitation of a single case study. Applying the same procedure in multiple case studies is a natural next step. As displayed in Figure 1, the research design comprises two more case studies, which are being concluded. This will allow us to test the validity and generalizability of the findings in a more systematic way. Furthermore, a thorough analysis of the feedback and recommendations from practitioners will enable the final consolidation of the MM. The expected output of Phase 3 is Version 2.0 of the HE-BIA MM. Finally, together with the EUNIS BI SIG, the authors also plan to roll out the model to the BI SIG group members across European universities for self-assessment of their BIA initiatives. Among other intentions, this work will also enable us to benchmark with some level of certainty the levels of BIA development in European HEI. This is a highly anticipated result for the EUNIS BI SIG members. The model and the result from such regional assessment could provide the governing body with useful knowledge to address the design of policies and continual improvement strategies at a regional level.

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APPENDIX A – THE HE-BIA MATURITY MODEL

Figure 7. HE-BIA maturity model (v. 1.0): technology part

HE-BIA Maturity Model (v. 1.0)

Technology Part:

Maturity levels for the dimensions in the technological area

		Level 1: Pre-adoption	Level 2: Initial	Level 3: Managed	Level 4: Systematic	Level 5: Optimized
Data (as a key asset)	*Dimension definition*					
Data Variety	How extensive are the variety of data used in analytics.	There is no BIA solution currently deployed.	The BIA platform supports structured data only. The BIA platform is optimized manually for structured data by the data warehouse team.	The BIA platform supports structured and semistructured data (e.g. XML and JSON). The BIA platform is optimized manually for structured and semistructured data by the data warehouse team.	The BIA platform supports all kinds of data including unstructured data such as documents, images, etc. The BIA platform is automatically optimized for some kinds of data in order to support analytics.	The data platform supports all kinds of data both internal and external data, with minimal operational overhead. The BIA platform is automatically optimized for multiple kinds of data in order to support analytics.
Data Velocity	How extensive is the velocity of data used in analytics (the speed at which analysts can access and leverage the data needs to match the speed at which it's created.)	There is no BIA solution currently deployed.	New data is available for analysis on a quarterly or semester basis.	New data is available for analysis on a monthly or weekly basis.	New data is available for analysis on a daily basis.	Data is available for analysis in real time as it becomes available.
Data Products	*Dimension definition*					
Traditional Data Products	Development and utilisation of reports, dashboards, scorecards, OLAP (online analytical processing) and data visualisation technologies to display output information in a format readily understood by its users, e.g., managers and other key decision-makers.	Only static and parameter-driven reports are available.	Business intelligence tools are in place for enterprise reporting. Ad-hoc reporting and OLAP are supported.	Enterprise-wide definitions are in place for key business metrics. Power users create data mashups from multiple sources.	Organizations have broad user access to BI using embedded dashboards within key applications and mobile BI. Users can perform ad hoc analyses and visualizations. Well-defined data dictionaries and data governance policies are established.	Organizations have established interactive and streaming BI dashboards for enterprise-wide KPIs. Business users are enabled to use BI tools to customize their view of the state of business and identify opportunities and risks through user-defined, custom alerts.
Advanced Analytics	Development and utilisation of sophisticated statistical and data mining/machine learning software to explore data and identify useful correlations, patterns and trends and extrapolate them to predict what is likely to occur in the future.	Currently not applicable.	Limited ability for statistical modeling, typically performed one-off.	Limited use of predictive and statistical modeling capabilities mostly through manual calculation and forecasting. Basic batch predictive models have begun to emerge.	Predictive models have been developed for multiple purposes such as student retention analysis and predictive maintenance for equipment. Organizations begin to develop prescriptive models that generate recommended actions for users based on analysis of data.	Predictive models are based on real-time data streams and update dynamically (e.g., real-time campus space occupancy). Models are deployed within key business applications to support real-time operational decision making and personalized recommendations. Data scientists have the ability to build, refine, and select the best model after having run multiple in parallel.
Technical Foundations	*Dimension definition*					
Architecture	How advanced is the BIA architecture?	Spreadmarts (Spreadmarts are spreadsheets or desktop databases that function as surrogate data marts. Each contains a unique set of data, metrics and rules that do not align with other spreadmarts, management reports or analytical systems.)	Multiple local (non-integrated) data marts (A data mart is a shared, analytic structure that generally supports a single application area, business process or department.)	The organization has a data warehouse in place, typically for structured data only.	The organization has a centralized data warehouse but is also investigating adding another platform to the centralized warehouse to analyze semi- and/or unstructured data.	The organization has a comprehensive enterprise data warehouse, and also leverages newer technology such as commercial Hadoop and enterprise NoSQL databases. New data sources are easily prepared and integrated into the enterprise DW.
Technical Integration	Techniques and best practices that repurpose data by transforming it as it's moved. ETL (extract, transform, and load) is the most common form of data integration found in data warehousing.	Simple ETL with no standards that just extracts and loads data into the DW, with simple tranformations.	Standardized ETL across different data marts (e.g., conformed dimensions and facts).	Advanced ETL, e.g. slowly changing dimensions manager, hierarchy manager, special dimensions manager, etc.	A standardized data quality system is in place. Initial steps are taken towards an extended DW environment through the use of data virtualization.	Optimized ETL for right-time DW with all the standards defined (near real-time if appropriate). Data virtualization is employed to extend DW into a modern analytical ecosystem.
IT Infrastructure	How well does the university's IT infrastructure support the depolyment of BIA solutions?	There is no need for IT infrastruture support due to the absense of a BIA solution.	Sufficient IT infrastructure support is given to sporadic BIA pilot projects. Accessibility and flexibility are key requirements to enable the timely development of BIA pilots.	IT infrastructure needs to support the deployment of BIA initial products (e.g., data marts), ensuring the security and reliability so that BIA products comply to the standards of the university's IT service management (e.g., SLA-service level agreements).	IT infrastructure needs to support the deployment of all spectrum of BIA products (e.g., DW/data marts and AI/machine learning) enabling their timely scalability whenever required.	IT infrastructure needs to fully support the deployment of all current and future BIA products, ensuring all requirements of flexibility, security, reliability and scalability of BIA products in a cost-effective manner.

Figure 8. HE-BIA maturity model (v. 1.0): organizational part

HE-BIA Maturity Model (v. 1.0)
Organization Part:
Maturity levels for the dimensions in the organizational area, including People and Processes

		Level 1: Pre-adoption	Level 2: Initial	Level 3: Managed	Level 4: Systematic	Level 5: Optimized
Value	*Dimension definition*					
BIA Strategy	Defining and managing the vision and strategy of the BIA solution, and how it supports the university's strategy. Example of strategies include being more predictive, aligning BIA with the "business"/academic stakeholders, and research new opportunities experimenting with new technologies and methodogies to drive the campus of the future (given the new data sources, tecnologies and analysis methods currently available).	There is no BIA strategy defined in the university to support financial, teaching or research related analytical aspects.	Only local and sporadic BIA strategies are defined (i.e., for faculties, departments, or services/offices). The local strategies are partially aligned or not aligned with the university (corporate) strategy.	The BIA strategy is defined at the university (corporate) level and is aligned with the strategy of different faculties and departments of the university.	There is a clear vision for the use of advanced analytics in key areas of the university.	The full strategic loop is complete, from planning, executing, monitoring and improvement of the BIA strategy - fully aligned with university goals to improve key focus areas (such as research, teaching, innovation).
Academic Analytics Support	Academic analytics refers to applying data analytics to aggregated levels (programs, departments/faculties, the institution, the national level) in order to provide input for policy-making (either internally or externality at national and/or EU level). This dimension describes the effective value of the BIA solution in supporting academic analytics.	There is no BIA solution currently deployed.	Inititial data products are developed, however, the BIA solution is not yet connected with any official performance management reports.	The support of the BIA solution to performance management is limited to anual academic year reports and linked with traditional reporting and statistics from Institutional Research offices.	The BIA solution supports university performance management with data at different organizational levels (university, faculties, departments, services/offices) and is used for operational decision-making with KPI measurement (and drill-down capabilities) leading to cost reductions in key business processes, the creation of new products (e.g., program management), identification of new customers (e.g., marketing campaings for student recruitment).	The BIA solution supports university performance management with data at different organizational levels (university, faculties, departments, services) and is used for near real-time operational decision-making with KPI measurement (and drill-down capabilities). The BIA solution also supports strategic decision making, enabling management and monotoring of the university's strategic goals (e.g., using a balanced scorecard).
Program / Project Management	*Dimension definition*					
Sponsorship	Level of sponsorship of the BIA solution; includes senior leadership support and responsibility. Important to secure adequate resources (e.g., funding, HR, organisational structure) and to set out the vision and strategy of the BIA solution.	There is no sponsorship of the BIA solution.	Initial data products are developed with the ownership and support of local areas (e.g., departments, admistrative offices) from the technical side, but there is no business sponsor from the university (i.e., an influential leader).	A business sponsor is apppointed at the university level (typically at the Rectory level) to coordinate all the BIA efforts at the university. A BIA director (program manager) is appointed to oversee all ongoing BIA projects, although still working part time for the BIA solution.	As the BIA solution evolves into a strategic asset for the organization, the level of sponsorship increases, with university leadership involved and working in close collaboration with the business sponsor and the BIA director (which now works full time for the BIA solution).	The highest level of sponsorship is the creation of a new dedicated unit/office to manage the BIA solution. This unit is typicallt called a BICC (Business Intelligence Competence Center) with a cross-functional team, integrating both IT and "business"/university members. The BICC is responsible for defining the BIA vision and strategy, securing and controlling funding, developing user skills, establishing standards, and building the technological blueprint for BIA implementation.
Data Governance	Level of adherence to data governance practices and methodologies, i.e., the effective application of principles, polices, use of data standards (for how data is modeled and exchanged), roles, responsibility and operational processes definition for data management across the organization, ensuring the quality and the accuracy of the data in the BIA solution.	There is no awareness of the need to establish data governance policies and metodologies.	There are no automatic controls on the data quality; no metadata and no preferred data standards in use. Local projects establish their own data management practices; possible sources of conflict are managed reactively and on case by case.	Initial policies and metodologies for data management start to be defined. Quality controls are enforced on less than 40% of data; metadata exists only for some data sources; no preferred data standards but are moving that way. Initial definition of roles and responsibilities (e.g., sponsors, user groups, committees, etc). Awareness of the need to appoint a data steward, to drive the organizational agreement on definitions, business rules, and to solve possible data conflicts between BIA projects.	Data management policies and metodologies are defined and stable. A data steward is appointed. Quality controls are enforced on more or less 80% of data; metadata exists for more than half of the data sources; and data standards are fully defined.	Data management policies and methodologies are fully defined and there is an explicit accountability of the BIA solution. Quality controls are enforced on all managed data; metadata for all the managed data; and data standards are in place. Developing new data products integrated into the BIA solution is now easier due to the clear data governance polices and methodologies.
Change Management	Ability to manage changes within the context of the BIA solution, in terms of user requests, achitecture, skills, user experience, etc. Any issue that impacts a BIA project's schedule, budget or scope should be considered a change.	There is no change management mechanism in place for the BIA solution.	There is the awereness of the need to manage BIA changes, athough a proper mechanism is not yet defined.	An initial change management mechanism is set in place (e.g., a change control log). Changes are partially documented.	A standardized change management mechanism is deployed and used by the BIA team. Changes are fully documented.	Changes are fully documented and communicated to properly adjust user expectations. Communication with stakeholders is also well managed, both with internal stakeholders (different user groups) as well as external stakeholders (national accreditation agencies, national Higher Education ministries, vendors, consultants, etc)

Figure 9. HE-BIA maturity model (v. 1.0): organizational part (continued)

HE-BIA Maturity Model (v. 1.0)
Organization Part: (cont.)

		Level 1: Pre-adoption	Level 2: Initial	Level 3: Managed	Level 4: Systematic	Level 5: Optimized
Business Process / BIA Development	*Dimension definition*					
Process Coverage	How wide does the BIA solution give support to the university value chain. Specifically: - how many of the key business process areas are impacted: Financial, Academic, Human Resources and Research; - and how many of the supporting business processes are impacted (e.g., IT, logistics, facility management).	The BIA solution does not formally support any of the key business process areas, nor any of the university's supporting business processes.	Initial data products are deployed supporting 1 key or supporting business process areas of the university.	Data products are deployed supporting 1 or 2 key business process areas of the university. The BIA solution supports 0 or 1 supporting business process areas.	Data products are deployed supporting 3 key business process areas of the university. The BIA solution supports 1 or 2 supporting business process areas.	Data products are deployed supporting all key business process areas of the university. The BIA solution supports 1, 2 or more supporting business process areas.
People	*Dimension definition*					
User Groups	Type of users that have access to the BIA solution (i.e., accessing users). Users are typically grouped into 4 structural groups: - Leadership: university top level management/Rectory, school/faculty level management, university central services, local school/faculty services management - Administrative staff: from university central services, local school/faculty services (or offices) - Faculty: professors, researchers - Students: current, alumni	There is no BIA solution currently deployed explicitly addressing the data needs from any of the 4 user groups.	User group access to the BIA solution: - Less than 25% of leadership - Less than 10% of administrative staff	User group access to the BIA solution: - Between 25% and 50% of leadership - Between 10% and 25% of administrative staff Awareness of the need for faculty and students user groups begin to have access to the BIA solution.	User group access to the BIA solution: - Between 50% and 75% of leadership - Between 25% and 50% of administrative staff - Less than 10% of faculty and students	User group access to the BIA solution: - More than 75% of leadership - More than 50% of administrative staff - More than 25% of faculty and students
System Usage	This dimension measures the effective usage of the BIA solution, determining the number of active users, considering the 4 user groups. The definition of an active user needs to be clarified for each organization (as an example, "active" entails at least one interaction with the BIA solution per month).	The BIA solution does not trace user access.	User access is traced. From each of the 4 user groups that have access to the BIA solution: - less than 25% of leadership - less than 25% of administrative staff are active users.	From each group of users that have access to the BIA solution: - between 25% and 50% of leadership - between 25% and 50% of administrative staff are active users.	From each group of users that have access to the BIA solution: - between 50% and 75% of leadership - between 50% and 75% of administrative staff - less than 25% of faculty and students are active users.	From each group of users that have access to the BIA solution: - more than 75% of leadership - more than 75% of administrative staff - more than 25% of faculty and students are active users.
User Capabilities	Profile of users in terms of BIA proficiency and data analysis literacy.	Users (from all user groups) do not possess BIA expertise, i.e., are not capable of analyzing and interpreting reports.	Initial proficiency level: reading and understanding. Leadership users are only able to interpret static reports. Administrative staff are only able to interpret static reports.	Average proficiency level: understanding and initial experiments with self-service BI. Leadership users have the competence to manage dynamic reports (specifically those with a technical background). Administrative staff are only able to interpret static reports.	Good proficiency level. Self-service BI enables users to build their own analysis. Leadership users have the competence to manage sophisticated reports and perform "pull" analysis. Administrative staff have the competence to manage dynamic reports. Faculty are able to interpret static reports. Students are able to interpret static reports.	Very good proficiency level. Complete self-service BI and initial experiments with advanced analytics. Leadership users have the competence to experiment with advanced analytics. Administrative staff have the competence to manage sophisticated reports and perform "pull" analysis. Faculty have the competence to manage dynamic reports. Students are able to interpret static reports.
Analytical and Decision-making Culture	Includes the promotion of a data-driven decision support and analytical culture across the university, i.e., how BIA contributes to decisions made throughout the university.	There is no awareness of the need to promote a data-driven decision making and analytical culture in the university.	The support of the BIA solution to decision making is very limited. Low level adoption of analytical thinking.	The university begins to encourage an analytical thinking and BIA solution is used to support decision making with data at some organizational levels (including faculties, departments, and services). Leadership users actively use the BIA solution to make decisions.	The university encourages an insight-driven culture and provide its members with an appropriate environment for the proliferation of this culture. The BIA solution is used to support decision making with data at all organizational levels. Leadership and administrative users can explore the data and make decisions with a data-driven culture.	The BIA solution is used to support decision making with data at all organizational levels, and to produce insights in real time. Users use the BIA solution and these real time insights and act on them on a timely manner. Faculty and students begin to have a data-driven culture.
Training	Competence improvement of the different set of users. Users of the DW/BI system must be educated on data content, BIA applications, and ad hoc data access tool capabilities (if needed).	There are no training programs to improve the BIA competences of users.	There is the awareness of the need to establish a systematic training program to educate users.	The BIA training programs are mainly focused on highlighting the importance and benefits of the BIA.	There are ad hoc BIA training programs focusing on specific issues. Specifically, users are educated about self-service BI.	There is a continuous BIA training program schedule in place. BIA training programs are designed to create more autonomous users, and power users that further contribute to improve competencies of the other users.

APPENDIX B - INTERVIEW GUIDE

Interview Key Sponsor Questions

Here are some of the questions for the interview with the key sponsor. The main purpose is to get an idea on the development of BI from a strategic point of view. It is going to be a relatively open interview.

1. What triggered the development of BI in NTNU?
2. Briefly take us through the BI journey at NTNU.
3. Please describe the BI technology used in your organization and the ways different departments/ units are using the BI components.
4. What are the main drivers and obstacles for further development of BI and analytics in NTNU?
5. Do you have any examples on BI assisting in making decisions at operational/tactic/strategic level?
6. In terms of BI and analytical dataset, toolset, skillset, and mindset, how would you position NTNU?
7. What is next? Any roadmap?
8. What would you like to share with the EUNIS BI community in terms of:
    a. critical success factors
    b. one or two advises for other universities that are starting to invest/investigate in BI and analytics

Interview Team Lead Questions

Recall the results together with the team lead and conduct a semi-structured interview with the following focus.

1. How do you get where you are today (history)?
2. Do you have any direct feedback regarding the MM assessment (use the feedback form (see Appendix C))?
3. Evaluate on the quality of the study in terms of
    a. the results
    b. the process
4. Reflections on the usefulness/value of the results and the process
5. The MM assessment, what next? Any Impact?
6. What will you do with this information (communicate with the rest of the team? Negotiate more budget? Revise plan/strategy)?
7. From MM assessment to roadmap, how? (for instance, what is the most immediate move? Which dimensions to touch? Any dependences?)

APPENDIX C - FEEDBACK FORM

Lean HE-BIA maturity model: Feedback form

Thank you for participating in this assessment. We would value your feedback regarding the following aspects.

1) Your opinions on the usefulness of this maturity model for your university.
2) Your opinions on the dimensions of the MM. Do these adequately capture the important dimensions for BIA initiatives in Higher Education Institutions?
   If you have any suggestions to improve the clarity of each dimension, please update Table A (next page).
3) Your opinions on the levels. Do these correctly capture the progression? How easy was the process of selecting the right maturity level for each dimension?
4) Your opinions on the high-level categories of the MM. If you have any suggestions to improve the clarity of each category, please update Table B (next page).
5) Any other comments.

Table 2. Specific dimension feedback

Dimension name	New name proposal	Additional comments
TECHNOLOGY		
Data variety		
Data velocity		
Traditional data products		
Advanced analytics		
Architecture		
Technical Integration		
IT infrastructure		
ORGANIZATIONAL		
BIA strategy		
Academic Analytics support		
Sponsorship		
Data governance		
Change management		
Process coverage		
User groups		
System usage		
User capabilities		
Analytical and decision-making culture		
Training		

Table 3. Specific category feedback

Category name	New name proposal	Additional comments
TECHNOLOGY		
Data (as key asset)		
Data products		
Technical foundations		
ORGANIZATIONAL		
Value		
Program /project management		
Business process / BIA development		
People		

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