A Work Project, presented as part of the requirements for the Award of a Master Degree in Management from the NOVA School of Business and Economics.

Digital Acceleration Index:

The relationship between firms' Digital Maturity and human capital

&

Digital Maturity trends in Portugal

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Abstract

The importance of having the digital means to adapt and survive digital disruption is a ubiquitous factor for firms in the 21st century. The Digital Acceleration Index (DAI) is a Digital Maturity Model developed by Boston Consulting Group (BCG). This project follows its first edition in Portugal, analyzing the results and exploring the relationship between Digital Maturity and gross salary through the lens of a multiple regression model while also providing a framework for analyzing and mapping out digital trends through text analysis.

Keywords: Digital Maturity, Digital Transformation, Human Capital, Maturity Model

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1 Introduction

The digital world has become increasingly interwoven with our own physical reality. The distinction between physical and digital has become blurred, with companies aiming to create end-to-end experiences, products and services that may start digitally and end analogically. Disruption has become ubiquitous and a cause of concern for consumers, firms and even entire nations. This shift in paradigm has seen new concepts and terminology, namely Digital Maturity, appear during the last decade, alongside attempts at measuring it based on broad ranging digital frameworks. Companies will find benefits in going digital and compete for ”digital supremacy” (Bloom and Pierri, 2018), in other words, companies who set digital transformation as a priority and see it through will reap the economic benefits and potentially be able to rise far above the competition. In fact, recent studies have highlighted the importance of going digital in order to enhance productivity (Gal et al., 2019).

Attempts at measuring Digital Maturity began in the early 2010s with domain-specific practitioner-based models based on empiric observation. Over the past decade, we have seen several digital maturity frameworks pop-up, both industry-specific and nationwide. However, most of these models fail to account for an important variable: the evolution of digital maturity over time.

The ultimate goal of this study is, firstly, to portray the state of Digital Maturity in Portugal, secondly, to see how that maturity influences the existing firms and thirdly, what digital transformation trends can be observed from Portuguese managers' inputs. Through the 2020 edition of the Digital Acceleration Index, a Digital Maturity Model developed by the Boston Consulting Group, and the first of its kind in Portugal, 1044 firms from several different industries are surveyed regarding 36 different digital topics (hereafter referred to as ”dimensions”) and the results are analyzed by economic sector and firm size. In what is ultimately a sparsely inhabited and still nascent field, this is the first step in accounting for Portuguese firms' Digital Maturity over the next decade. Following that, the digital maturity results are crossed with nationwide statistics regarding wages, education, and employee age, among others. Based on these variables, a multiple regression model is developed in order to assess the relation and impact between Digital Maturity and Wages. Lastly, in order to further understand the trends surrounding the topic in Portugal, a qualitative framework has been created for the analysis of keywords in Digital Maturity through wordclouds and through network structure analysis.

This project starts out by going through the existing literature regarding digitalization, namely, some of the concepts and challenges in defining and measuring digital maturity and what has been researched about the Portuguese economy. Then, the methodology behind the DAI survey data collection and cleaning is briefly explained and an overview of the National Workforce Data set is given. Following that, results from the survey and the subsequent analysis are presented and interpreted. Finally, the results are contextualized in the existing literature and limitations of the study are presented along with potential future developments.

2 Literature Review

2.1 Defining Digital Maturity

When discussing the transition from the physical to the digital world, technical terms like Digitalization and Digitization are frequently used interchangeably. However, some scholars have made an effort to define these topics in a more precise and nuanced way. Brennen and Kreiss (2016) base their definition on the Oxford English Dictionary's entry, stating that digitization consists of any process of converting analog information into "digital bits of 1s and 0s" while Digitalization refers to the general adoption of technology in many domains of society. Thusly, from a management perspective, one can see an example of digitization when a firm migrates their transaction records previously kept on paper to digital. Digitalization, on the other hand, can be seen in new product or service offers or even broader changes to a firm's Business Model in order to adapt and adopt new available technologies and improve performance (Racinger et al, 2018).

The definition of digital maturity is often blurred by differences in perspectives (Aslanova and Kulichkina, 2020). At its core, it aims to represent the status of a firm at a given time, not only through its current processes and adoption of new technology but also in its flexibility and preparation in adapting to future changes. Often disruptive, they represent shifts in paradigm as seen through so-called "soft" digital attributes - attributes such as corporate culture, leadership and governance, among several others. Digital Maturity is, therefore, a way of assessing the progress of a given company in its digital transformation process (Teichert, 2019).

Mapping out the path undergone by firms is an imprecise challenge. Teichert's (2019) systematic review of more than 20 Digital Maturity Models (DMMs) reveals that there is no consensus regarding the nature and definition of digital transformation. Furthermore, variations occur at many different levels. They appear between practitioners and academics, between general and domain-specific approaches and also based on the underlying digital framework and roadmap.

One of the most poignant differences when reviewing DMMs are based on whether a model is Academic or Practitioner-based (Felch et al., 2019). This is true both in matters of substance - science-based models are more descriptive in nature when compared to the prescriptive nature of practitioner DMMs.

The first models considered by Teichert (2019) were all practitioner-based, with academic DMMs being published only years after. In light of this, academic models built on top of the groundwork defined by practitioner-based models. Either one is based on empirical data/observation.

Teichert (2019) also gives us the definition of dimension as a “specific, measurable and independent component which reflects a major, fundamental and distinct aspect of digital maturity” and in his systematic review of 22 digital maturity models, he finds that all of them assess between 4 and 9 dimensions, of which the most common are: “Digital Culture”, “Technology”, “Operations & Processes” and “Digital Strategy”. On the other side, there is a distinct lack of attention given to the “Business Model” dimension, with only 3 out of 22 models assessing it.

It is also worth mentioning that, despite culture-related dimensions being present throughout most models, there is an inconsistency as to what culture attributes should be assessed and if the information collected is reliable. Buvat et al. (2017) expose the huge disparity between what the senior executives think of their firm’s digital culture compared to what the employees think. For example, in France, 45% of surveyed leaderships thought that there was a strong digital culture in their organization, contrasting with the 3% of employees in agreement with that statement.

Another point of contention is the lens through which Digital Maturity progress can be assessed. Some studies view Digital Maturity as a linear process that undergoes a set number of stages, as seen with Berghaus and Back (2016) and Leyh et al. (2016), among others. In practical terms, what these studies seem to have in common is an attempt at mapping a firm’s unique configuration to a defined stage of Maturity, measured across the variables within the scope of the model. The stages vary between models, for example, the authors above consider 5 and 4 possible stages respectively while Strategy&’s “Measuring industry digitization” (Friedrich et al., 2011) splits firms into 3 stages (laggards, midfield and leaders). In spite of the nuance imbued in each of the models above, these stages convey approximately the same in regards to maturity. In contrast, non-linear models view Digital Maturity as a fluid state, resulting from a mix of different qualities that don't necessarily progress in a fixed order. Remane et al. (2017) further expands on this notion by suggesting a framework that takes a firm's Digital Impact (the effect of digital transformation) and Digital Readiness (the preparedness to tackle disruption and undergo further digital transformation) into account, offering 4 possible configurations conveyed through a 2x2 matrix. This view offers a dynamic configuration, but has the disadvantage of complicating the process of ranking different firms.

Conversely, regarding the measurement of the maturity level, most studies seem to mimic the same method, relying on surveys and self-assessment descriptions to collect information about the respective firms (Barata and Cunha, 2017). Most of the bigger surveys are conducted periodically by major consulting groups such as PWC's Industry 4.0 report, KPMG's Digital Readiness Assessment or Deloitte's Digital Maturity Model.

While this project is focused on the digital maturity of enterprises operating in Portugal, it is relevant to investigate what has been researched regarding the impact and challenges of "going digital" in the business world and how these insights can apply to the Portuguese economic landscape.

As previously mentioned, most of the major digital maturity surveys and analysis are done by Consulting groups and more recently there have been some academic papers focusing on the subject. However, Portugal seems to have a research gap in DMMs, having no major practitioner or academic analysis of the economy's Digital maturity . In fact, most of the existing information about the Portuguese economy's digital level is from studies done by European Union and government entities.

Such is the case of the Digital Economy and Society Index (DESI), a yearly report on the degree of digitalization of each of the 27 member states plus the UK, that focuses on 5 dimensions (each with a different score): "Connectivity", "Human Capital", "Use of Internet services", "Integration of Digital technologies" and "Digital public services". Results from 2020 showed that despite being above the EU average in Connectivity and Digital public services, Portugal is quite behind the curve when it comes to (a) Human Capital (21st out of 28), mostly due to having a large percentage of people who have no digital skills (26%) and lacking a significant percentage of ICT graduates (only 1.9% of all college graduates) and (b) Use of Internet Services (24th out of 28) by having a large percentage of the population that has never used the internet (22% vs. EU average of 9%).

Additionally, the lack of knowledge can also be observed in a managerial sense, as many Portuguese managers don't know how and where to implement digital improvements in their firms and lack awareness of the respective potential benefits which, in turn, leads to low willingness to invest and a low adhesion to existing public financing programs (European Investment Bank. 2019).

Effectively, this digital literacy gap in the Portuguese economy seems to be in line with the findings from other reports that also point this out as a decisive factor for the country's divergence from the EU average.

2.2 Impact of Digital Maturity on firm outcome

The Covid-19 Pandemic and economic duress stemming from national lockdowns brought to the limelight the importance of being up to date with all the technological tools, highlighting the severe shortcomings in many companies and industries that failed to catch up with new advancements in Information and Communications Technologies (Baig et al., 2020; Fletcher and Griffiths, 2020). According to Summa (2016), a firm's adaptability and reaction time to sudden change might be make-or-break factors in its success. Naturally, this agility is often tied to a company's digital prowess.

Effectively, surveys and data from the past year seem to show how companies have been pushed by the pandemic to transform their businesses. A majority of these firms also view this shift as long-lasting transformation instead of a temporary adjustment.

At first glance, the path to digital maturity seems like an obvious choice for any company looking to grow. There is extensive research detailing the benefits of going digital on channels such as Marketing (Kannan and Li, 2016), Big Data management (Wamba et al., 2014), Industrial processes (Dalenogare et al., 2018) and Supply Chain management (Büyüközkan and Göçer, 2018). Grebe et al. (2018), who followed the performance of a group of firms over 3 years, also point out that digitally mature companies outperform their peers in metrics such as Time to Market and Cost efficiency.

However, Fletcher and Griffiths (2020) warn against introducing new technology as a knee-jerk reaction before doing their due diligence. When lacking required infrastructure and readiness, these could instead pose a threat to the firm, as is the case of cybersecurity. Recently, firms without videoconferencing capabilities resorted to consumer grade messaging applications as a solution. While seemingly innocent, these actually represent a threat to company data and are potentially non-compliant with European Data Protection Laws. Furthermore, they also reflect poor digital governance.

Therefore, it is not correct to assume that an enterprise should just invest blindly in digitalization and expect to have widespread gains. In fact, even under good conditions, not all digital investments net the same return. A model done by McKinsey Digital (Bughin et al., 2017) attempted to measure the average return on investment for different digitalization efforts and found that investing in digital Products and Processes seems to offer a bigger increase in revenue (3.5% and 3.2% respectively) when compared to digitalization attempts in Supply Chain (2.3% increase).

To sum up, digitalization is a complex process that requires more than the mere adoption of new technologies. A company must also have a solid foundation in terms of work methods and organizational agility in order to adapt quickly and have human capital that is skilled and up-to-date with new ICT (Frey and Osborne, 2013). Additionally, Dalenogare et al. (2018) take it a step further and point out that the external environment (here defined as the general level of digital maturity of the surrounding economy) is also a key determinant to the success of digital transformation, namely in developing countries that often lack the digital infrastructure to support state-of-the-art digitalization.

In fact, some researchers argue that the new digital transformation wave has contributed to create a larger gap in firm performance since the companies that are better suited to have productivity benefits from digital improvements, are already the most productive in the first place (Gal et al., 2019). This can create a virtuous cycle for the digital leaders by attracting the highest skilled workers since digital maturity has also been associated with an increase in skilled labor (Bartel et al., 2007) due to the way it helps automate repetitive tasks and create more challenging job positions. That being said, since some studies have pointed to a positive relationship between productivity and salaries (Laskina et al., 2020) one could theorize that digital maturity might have an indirect positive influence on salaries due to productivity gains. Based on the research done on the literature, there doesn't seem to be any major publications answering this question directly apart from a study from 2001 surveying a group of Taiwanese manufacturing firms that found significant results confirming a positive relationship but with the caveat that results might differ from country to country (Liu et al., 2001).

3 Methodology

This project relies on two main data sets for its analysis: the results from a survey sent out to Portuguese companies, collected by Nova School of Business and Economics and the Instituto de Marketing Research (IMR), and a nation-wide census of the Portuguese Workforce data for 2017 provided by the Instituto Nacional de Estatística (INE).

The survey data is comprised by both rating questions and optional open-ended questions in regards to those, therefore providing a plethora of contextual data in addition to the scores used to calculate the Digital Acceleration Index.

3.1 Digital Acceleration Index (DAI)

The Digital Acceleration Index is a metric used to evaluate a firm's digital maturity over time. Unlike other metrics, which measure the state of digital maturity at a fixed point in time, the goal of the Digital Acceleration Index applied at a national scale (DAI@Scale) is to construct a comprehensive image of an economy's digital maturity as well as its evolution.

It is a practitioner-based model created by the Boston Consulting Group's (BCG) based on their holistic digital framework. The first iteration of the DAI@Scale took place in Singapore 2019, and similar editions of this survey are being made in other countries. In the interest of measuring digital maturity over time, this survey should be the first of a systematic effort to record and document the evolution of Portuguese companies' digital maturity every couple of years.

3.1.1 Definition

Like most Digital Maturity Models, the Digital Acceleration Index attempts to measure all facets of a company end-to-end. It contemplates 36 different dimensions divided along 6 major blocks, as seen in Figure 1. The formula for the DAI itself corresponds to the arithmetic average of these dimensional scores converted to a scale from 0 to 100:

$$DAI = \frac{1}{n}\sum_{i=1}^{n} a_i * 100/4$$

Where n is the number of dimensions (34, 35 or 36) applicable - the Manufacturing and Shared Service Centers are firm specific - and a is the score from 0 to 4, the former used in cases where the respondents were unable to answer a question.

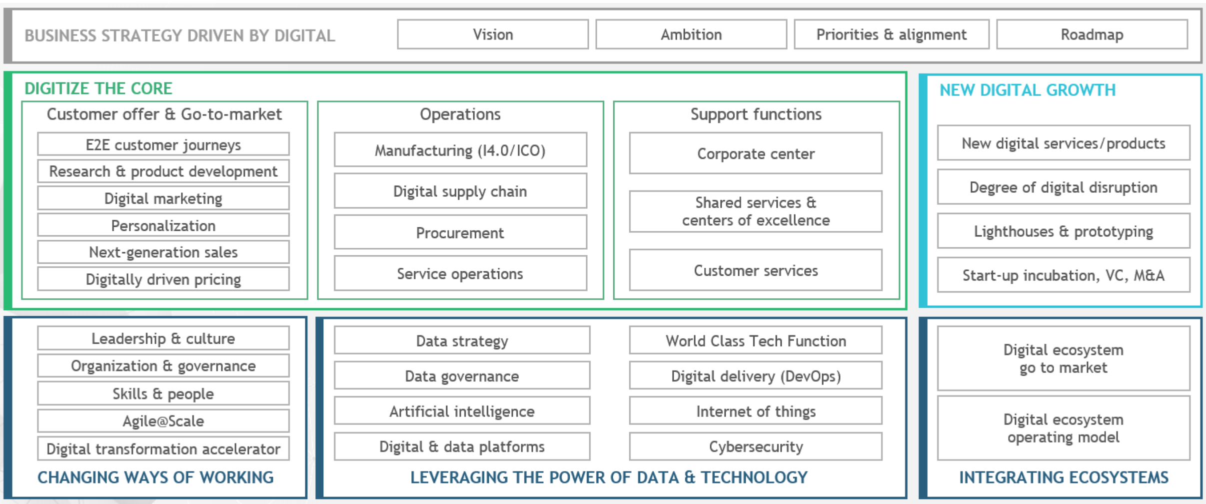

Figure 1: Boston Consulting Group's Digital Holistic Framework

The first block, "Business Strategy Driven by Digital", starts by assessing whether a company's overall business strategy has Digital at the forefront of it or whether the company at least admits the importance of having a clearly defined goal and respective roadmap communicated across its entirety.

The second and largest block is "Digitize the Core", which encompasses all the "essential" business sectors and is divided into 3 sub-blocks: "Customer Offer & Go-to-market", which assesses the degree to which a company is using digital solutions to enhance their customer journey, marketing and sales; "Operations" which focuses on the presence of Industry

4.0 technologies in manufacturing and supply chain and ”Support Functions” which measures the rate of Robotic Process Automation (RPA) or Artificial Intelligence (AI) usage in repetitive and high-volume activities such as customer service, accounting, and payroll.

The third block, ”New Digital Growth” is dedicated to Digital Innovation. Namely, it looks into how the firm uses the digital space to develop new products and services and how that development process takes place. Additionally, it also inquires about inorganic development through M&As and start-up incubation/investment.

”Changing Ways of Working” is part of a broader set of blocks dubbed the ”enablers”. It focuses both on the overarching work style as well as the hiring and retention of digital talent. Furthermore, it also encompasses dimensions related to company culture and to whether Digital is cascaded top-down from the board of directors to the rest of the workforce.

The fifth block is ”Leveraging the power of Data & Technology”. Comprised of 8 dimensions, this block gives us an overview of if and how the company uses data as a driver for growth. Ranging from overall data strategy & governance (e.g. does the company have a dedicated Chief Data Officer) to more nuanced areas such as Internet of Things (are there dedicated teams for development of use cases), Artificial Intelligence (is AI integrated in the decision-making process) and Cybersecurity (is it deployed on an ad-hoc basis or is the company taking preemptive measures and actively looking into its own vulnerabilities).

The last block of the enablers and the framework itself is ”Integrating Ecosystems”, which focuses on the existence (or lack thereof) of Digital Ecosystems between the responding firm and its business partners.

3.1.2 Survey/Data Collection

For each of the 36 dimensions, respondents were asked to rate their company’s Digital Maturity level for both their current state (2020) and their expected future state (2022) in an ordinal scale from 1 (“Digital Starter”) to 4 (“Digital Leader”), with two intermediate options (“Digital Literate” and “Digital Performer”). Each of these dimensions were accompanied by a custom description specifying several practices or standards expected from a company on each of those stages. The respondent was also asked to rate the importance of the question for their organization from a scale of 1 (low importance) to 4 (high importance). For all these questions, there was also a 5th option ("Don't know") that would allow the respondent to skip ahead.

Respondents were also encouraged to provide further detail on each of their answers through open-ended questions; one inquiring about the respondent's chosen score for its current state and another asking why the company had yet to arrive at the expected future stage in 2022. These questions totaled 180, or five questions for each of the 36 dimensions.

The complete survey also included three initial questions pertaining to the responding company's sector, geographical location and number of workers, two yes or no questions regarding the existence of logistics services or shared services center within the firm and 7 additional context specific questions unique to Portugal and its framing within Europe. This included topics such as employee development, financing options and an open-ended question regarding major challenges faced in the path to digitalization, bringing the total tally of questions in the survey to 192.

As previously mentioned, survey results were collected by two entities: Nova School of Business and Economics' Masters students in collaboration with Nova Junior Consulting and the Instituto de Marketing Research. In the surveys collected directly by the former, each respondent, upon agreeing in principle to participate in the study, was invited to a 30-minute video conference call to be introduced to the goals and objectives of the survey and study. These meetings also served an important second purpose of assuaging participant's concerns regarding privacy and anonymity. Videoconference calls were conducted with at least one person from within the organization - typically the Single Point of Contact (SPoC) - but would often include other stakeholders from within, including cross-disciplinary teams tasked with answering the survey. Respondents would then be given a printable version of the survey for internal use, a link to the survey submission itself and a copy of the presentation deck used in the presentation call. Students would also be available for further follow-ups and direct help in filling out the survey.

3.1.3 Survey Data Cleaning & Outlier Analysis

Unlike the group handled by Nova School of Business and Economics and BCG, most of the firms did not get such rigorous mentoring and support in the process of filling the survey. Therefore, there were a few entries that proved to have little use for any significant analysis, either because many questions were left unanswered or because the survey wasn't taken seriously. Consequently, some data cleaning was necessary to get a valuable sample.

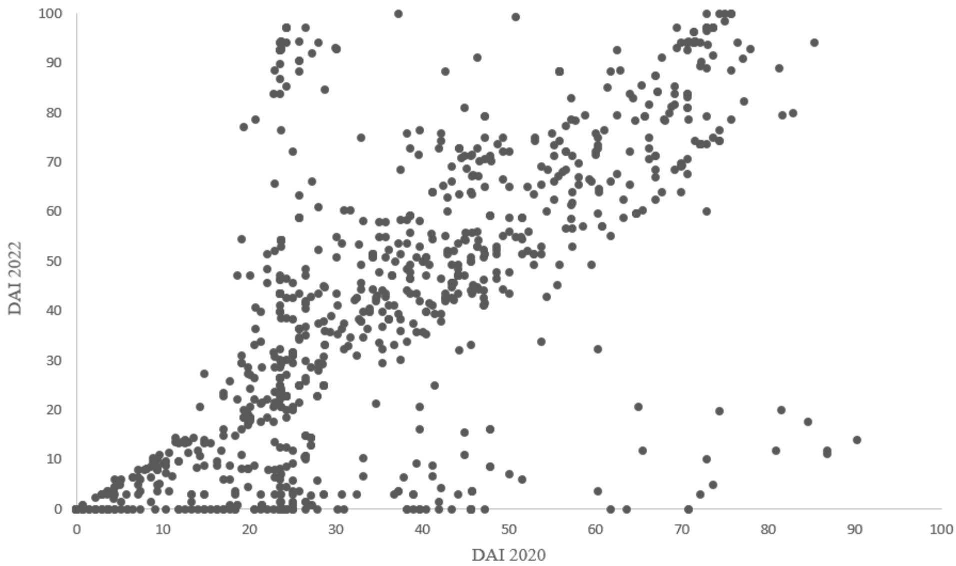

Figure 2: DAI Score 2020 and 2022 expectations

When taking a first glance into the plot above , instantly there were some oddities to be noticed. First of all, since the DAI score expectations for 2022 are on the Y axis and the 2020 DAI scores are on the X axis, all dots below the identity line (Y=X) were potential outliers, since they implied that the responding company expected their digital maturity to decrease over the next 2 years. Upon closer analysis, the reason for this was that many respondents did not fill in an answer for their 2022 expectations, causing a negative distortion of the results. Therefore, the 2022 DAI scores for these companies were discarded, which resulted in a decrease in the 2022 sample from 1044 entries down to 554.

Secondly, we decided to eliminate all entries that failed to answer more than 20 dimensions, out of the total 36. Consequently, our 2020 sample decreased from 1044 to 797 and our 2022 sample decreased to 512.

Lastly, some entries represented highly unrealistic expectations of improvement for such a short period of 2 years, with some respondents aiming to jump as much as 70 DAI points from 2020 to 2022. After looking at the companies selected by Nova which represented some of the portuguese digital leaders and arguably the ones with the biggest capacity to mature digitally in the near future, we decided to cap the DAI gap at 27.5 points, which is the highest expected jump from that pool of companies. Again, this removal only affected 2022 entries, reducing them from 512 to 399.

In conclusion, our final sample was comprised of 797 entries for the DAI in 2020 and 399 entries for the 2022 DAI expectations.

3.2 Data Merging

3.2.1 National Workforce Data

The National Workforce Data is a comprehensive country-wide census of employment and workforce statistics compounded by the Portuguese Instituto Nacional de Estatística (INE).

The dataset includes information about 290.407 firms operating in Portugal in 2017, both from the employer and employee perspective. Regarding employers, it includes information regarding firm age, size, revenue, sector of activity, number of employees, etc. From the employee side, it includes age, education levels, wages, tenure, among others.

In order to compare the DAI results with the Workforce Data, the mean values for each of these variables were grouped firstly according to each Firm's activity sector (CAE denomination) and then by size (per number of employees). Likewise, the same grouping method was used on the DAI sample, resulting in a final dataset of 15 different economic sectors further subdivided by 3 different size categories based on the survey question regarding number of workers: companies with 1 to 50 workers were classified as ”Small”, 51 to 250 were ”Medium” and those with over 250 workers were classified as ”Big”. The distribution of the 797 DAI companies can be seen in the table below.

Table 1: Merged Data distribution by Sector and Size

Sector Code	Sector Description	Big	Medium	Small
A	Agriculture & Animal Husbandry	1	2	10
C	Manufacturing Industries	22	54	119
F	Construction	4	10	39
G	Wholesale & Retail	11	45	115
H	Transportation & Logistics	8	11	15
I	Hospitality & Tourism	6	20	55
J	Information and Communication Technologies	8	14	36
K	Financial Services & Insurance	9	-	-
M	Consulting Services	2	-	-
N	Administrative & Support services	9	10	70
O	Government Administration & Defense	1	-	-
P	Education	2	7	27
Q	Healthcare & Welfare	3	9	41
R	Arts & Sports	1	-	-
S	Other Services	1	-	-

3.2.2 Multiple Regression Model

With the aim of analyzing the relationship between Digital Maturity and Human Capital (more specifically wages), a multiple regression model was developed through the Ordinary Least Squares (OLS) method. All regressions were estimated through the econometric software GRETL, always controlling for Heteroskedasticity through robust standard errors (variant HC0). The model was based on the following specification:

$$ln(Wages) = \alpha + \beta \ Adjusted \ DAI_i \ + \gamma X_i + \epsilon_i$$

On the left hand side, the natural logarithm of wages was used in order to observe results as a percentage change.

On the right hand side, the most relevant coefficient is β, since it represents the impact of Digital Maturity on the average Portuguese salary.

Additionally, there is also the coefficient γ which pertains to the vector of control variables (X_i). This vector contains variables that have been object of extensive research and proven to influence wages, based on economic theory. Firstly, on the Human capital side, employee tenure, age and education (the latter was assessed by the percentage of employees with a bachelor's degree) are all used following the widely known Human Capital Earnings Function (Mincer, 1974), which places earnings as a function of education and work experience. Secondly, since research has shown that hours worked increase when there is an expectation of a future increase in earnings (Bell and Freeman, 2001), average regular hours and average overtime hours worked were both added as control variables. Lastly, for many decades, a bigger firm size has been associated with higher wages due to various factors such as productivity, and economies of scale (Oi and Idson, 1999) and even though some research suggests that this effect has been dwindling over the years (Bloom et al., 2017), it is still relevant to control for it, therefore, Gross Revenue was added as a proxy variable for firm size.

As for the Digital Acceleration Index , since answers left empty were counted as 0, there was a certain negative distortion of the final scores. Therefore, in order to more precisely see how companies rated their digital maturity, another metric of the index was developed under the name "Adjusted DAI". In this case, the only difference when compared to the regular DAI score is that Adjusted DAI is calculated by dividing the sum of answers by the number of dimensions the respondent effectively answered instead of simply dividing by 36. The formula goes as follows:

$$Adjusted\ DAI = \frac{1}{n - empty\ dim} \sum_{i=1}^{n} a_i * 100/4$$

4 Results

4.1 Survey Results

The following table contains the summary statistics for the survey results both for the current Digital Maturity state (DAI 2020) and for the expectations for 2022.

Table 2: Summary Statistics for the Digital Acceleration Index

	Minimum	Maximum	Mean	SD	n
DAI 2020	16.91	90.28	40.79	18.09	797
Expectations 2022	20	94.28	57.30	19.32	399
Adjusted DAI 2020	25	100	46.43	20.49	797
Adjusted Expectations 2022	25.76	100	65.71	21.02	399

The average DAI Score for the 797 observations was 40.79, which corresponds to a 1.69 in the 1 to 4 scale, placing the Portuguese economic landscape in the ”Digital Literate” category according to BCG's nomenclature. However, given the diversity of the sample in terms of industries and firm size, it is necessary to breakdown the results in order to paint a correct picture of Digital Maturity in Portugal.

Firstly, looking into the differences in firm size and following the previously defined categorization, in the original sample, the distribution was 99 Big companies, 216 Medium and 729 Small ones, which after the outlier removal were then reduced to 88 Big, 182 Medium and 527 Small companies, therefore keeping a similar distribution to the originally intended one.

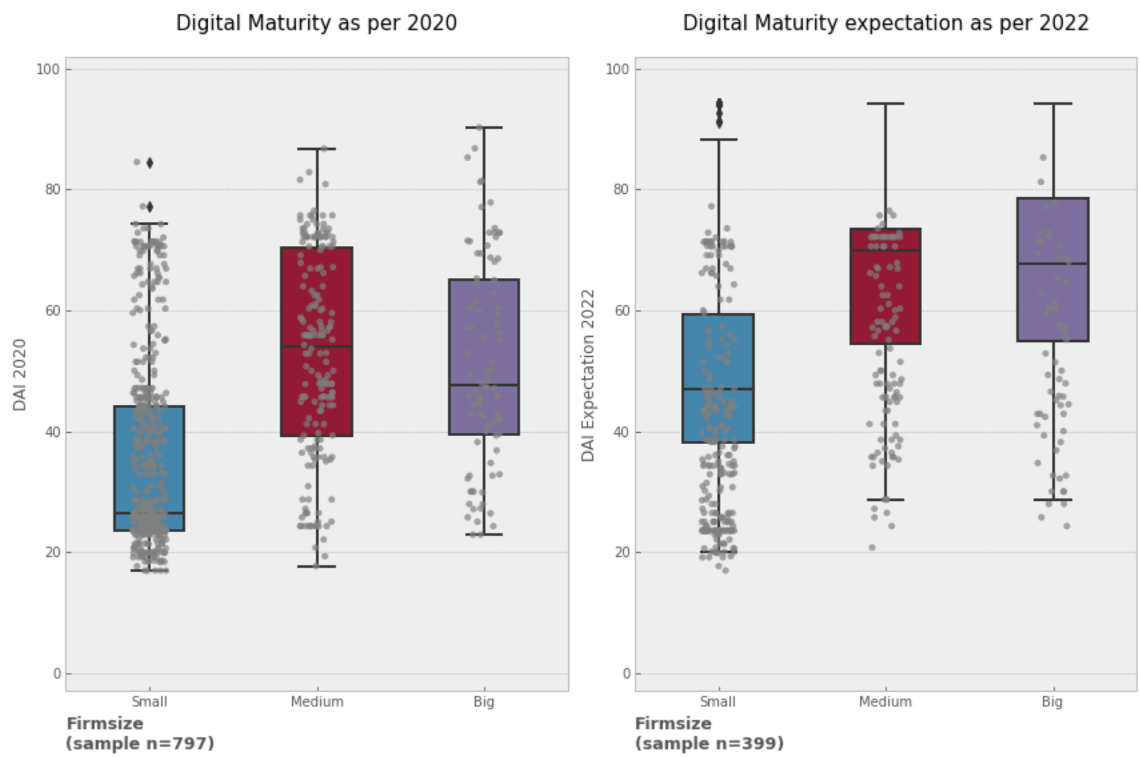

Figure 3: Dai Score distribution by size

In regard to how these unequal sized companies differ in terms of Digital Maturity, the plot above shows that there is a clear difference from the Small firms block compared to the rest of the pack. Presenting an upper quartile only a few points above the lower quartile for the other 2 sizes, both in 2020 and in 2022 expectations, Small firms seem to be at a digital disadvantage to their peers. On the other hand, Medium and Big corporations do not exhibit such strong contrast. When it comes to 2020, Medium companies presented a bigger median score and upper quartile compared to Big ones, but a very similar average score (52.6 and 51.5, respectively). Conversely, regarding expectations for 2022, Big companies seem to stay ahead in upper quartile and average score (67 points, against 65.5 from Medium sized firms), while still having a slightly smaller median score.

In order to do a sector analysis, the *Classificação Portuguesa de Atividades Económicas* (CAE), an economic activity classification used by the Portuguese National Institute of Statistics (INE), was used to delimit the different industries. In the next table, one can see the sectors that had more than 5 observations and how their average Digital Maturity compares to one another. The original distribution of the 797 firms per sector and size can be seen in Table 1.

Table 3: DAI results by Economic (CAE) Sector

	DAI 2020	DAI 2022	Adj. 2020	Adj. 2022	N
Agriculture & Animal husbandry	29.34	42.61	32.96	47.92	13
Construction	34.64	53.07	39.40	61.06	52
Wholesale & Retail	37.68	56.29	41.93	62.86	171
Hospitality & Tourism	37.88	59.57	43.09	68.54	81
Manufacturing Industries	39.80	53.53	45.14	61.96	195
Healthcare & Welfare	39.93	46.93	45.34	53.71	53
Education	38.92	65.02	45.52	76.44	36
Transportation & Storage	43.50	58.95	48.89	67.11	34
Administrative & Support services	43.26	60.59	49.64	68.45	89
Information and Communication Tech	60.10	70.99	70.58	83.87	58
Financial Services & Insurance	45.38	67.57	53.24	79.44	9

(2022 values are expectations as of 2020) Adj. = Adjusted DAI

At a first glance, it should come as no surprise that the sector with the highest digital maturity is Information and Communication Technologies (ICT) with an average score of 60 coming from a sample of 58 tech companies. This score places them in the Digital Performer bracket [50-75], making it the only sector in Portugal to achieve this feat. Perhaps more impressively, using the Adjusted DAI score, ICT has an average score of 70 which places the sector close to reaching a Digital Leader status. This pole position is further noticeable when looking at the gap from ICT to the sector coming in second: ”Financial Services & Insurance” which pales in comparison by lagging 15 DAI points behind, standing at a score of 43. Interestingly, the remaining sectors do not seem to differ a lot in their scores between each other with only 16 DAI points separating the second place sector from the last place one (Agriculture & Animal Husbandry).

When it comes to the predictions for maturing digitally in the coming years, the Education industry is the one that stands out the most by expecting an average jump of 26 DAI points, a whole DAI level, from 38.9 (2020) to 65 (2022). On the other end, the Healthcare & Welfare sector predicts only an average 7 DAI point increase in the two year period, making it the less optimistic expectation out of the sample. Interestingly, the industry with the second highest expected increase is Financial Services & Insurance, with a 22 point jump that would significantly shorten the gap between it and the ICT industry which, despite a small expected increase (10 points), would still be number one according to their expectations.

Finally, it is also relevant to look into how Portuguese firms performed in each of the different blocks of the survey. For this analysis, the Adjusted DAI Score was used to control for the differences in questions left unanswered, since some blocks had a higher average of blank answers.

The Adjusted DAI scores by block, as seen in figure 4, reflect that there aren’t any major differences in the distribution of digital maturity. Standing slightly above the rest, the block with the highest average score was Strategy Driven by Digital (48.7 Adjusted DAI points) which may suggest that a considerable amount of Portuguese business leaders are aware of the importance of digital transformation and of having a detailed plan regarding how to achieve it successfully.

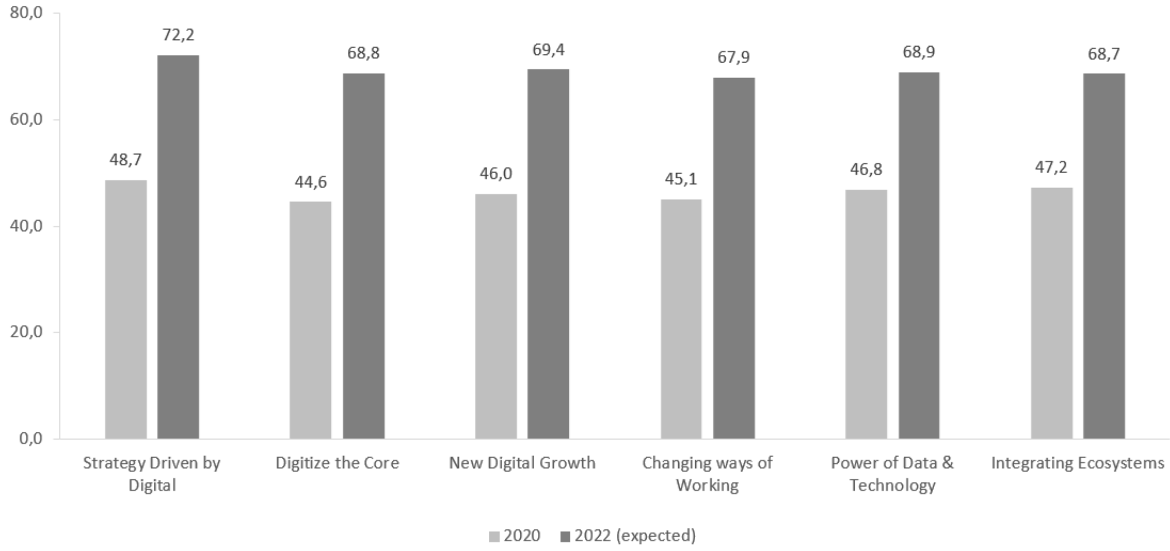

Figure 4: Average Adjusted DAI Scores by block

Furthermore, this block also takes the prize in the expectations for 2022 with an average adjusted score of 72.2.

On the other end, the lowest scoring block was Digitize the Core (44.8), in part due to the presence of the two lowest scoring dimensions out of the 36 total: Industry 4.0 (average of 38.2) and Supply Chain (40.6). Both these dimensions included a strong component of automation, and Internet of Things (IoT), therefore suggesting that there is still a long way until Portuguese companies see these practices as the new normal.

4.2 Regression Model Results

After analyzing the results from the DAI, this project aims to assess the influence of Digital Maturity on employee wages. Starting off this section, an overview of descriptive statistics of the final sample (Table 4) is presented. Consecutively, a correlation matrix between the different variables is discussed. Finally, as a predictive analysis, a multiple regression model is used to explain the relationship between the dependent variable and the explanatory variables.

Table 4: Descriptive Statistics for the Regression Variables

	Minimum	Maximum	Mean	SD
Adjusted DAI 2020	25.36	67.71	45.64	11.89
Regular Hours Worked (Month)	122.30	163.70	151.42	8.78
Overtime Hours Worked (Month)	0.08	14.24	1.80	2.70
Employee Tenure (Years)	2.90	19.89	7.62	3.33
Employee Age (Years)	34.91	48.77	41.26	3.20
Gross Revenue	0	554 904 537	48 946 202	102 956 244
(Log) Gross Revenue	12.10	20.13	15.86	2.33
% Employees w/ Bachelor's	4%	54.3%	22%	16.6

Table 4 provides some descriptive statistics regarding the variables used in the multiple regression model.

As mentioned before, this final sample is comprised of average values for 35 different pairs of Economic Sector-Firm Size entries (see Table 1), therefore the number of observations for each variable is 35, except for the natural logarithm of Gross Revenue, where it is 34 since there is one entry for Government firms, which have no revenue. The natural logarithm of Gross Revenue was used in order to interpret the results as a percentage change, given that average values were in the millions of euros.

Correlation Matrix

Correlation coefficients, using the observations 1–35 (missing values were skipped)

5% critical value (two-tailed) = 0.3338 for n = 35

RegHrs	OTHrs	EmpAge	EmpTen	AdjDAI	%Bsc	GRev	Wage	
1.0000	0.1278	−0.1189	0.2206	0.1424	0.1654	0.1463	0.3358	RegHrs
	1.0000	−0.0580	−0.1081	−0.1040	−0.3486	0.0116	−0.0743	OTHrs
		1.0000	0.5245	−0.4244	−0.1129	−0.2232	0.0115	EmpAge
			1.0000	0.1093	0.3761	0.2669	0.6488	EmpTen
				1.0000	0.4951	0.1571	0.4733	AdjDAI
					1.0000	0.2774	0.6440	%Bsc
						1.0000	0.4009	GRev
							1.0000	Wage

RegHrs = Regular Hours Worked; OTHrs = Overtime Hours; EmpAge = Employee Age;
EmpTen = Employee Tenure; AdjDAI = Adjusted DAI Score;
%Bsc = Percentage of employees with Bachelor's; GRev = Firm's Gross Revenue;

Going through the Correlation Matrix above, one can see that there are not any strong correlations between the independent variables, with the highest being between Employee Age and Employee Tenure ($r = 0.5245$), which is to be expected due to the chronological nature of both variables. As for the dependent variable Wages, it exhibits moderate positive linear correlation with both Employee Age ($r = 0.6488$) as well as with Percentage of Employees with a Bachelor's degree ($r = 0.6440$), which, again, is to be expected due to the influence that education and experience have on wages.

Regarding the Digital Maturity variable, a moderate positive correlation can be observed with Wages ($r = 0.4733$), indicating that there is in fact a positive relationship between the two, and also with the Percentage of Bachelor Degrees variable ($r = 0.4951$), suggesting that Digital Maturity increases alongside with Employee education (and vice-versa). On the other hand, the only remarkable negative correlation from the DAI variable comes from the pairing with Employee Age ($r = -0.4244$) , most likely stemming from the aversion to technological progress that older employees tend to exhibit, which translates to a slower Digital Transformation (Schulz, 2019).

Testing Hypothesis 1: The proposed hypothesis rests on the question of how digital maturity and digitization relate to wages, given the Portuguese economic landscape. It is hypothesized that there is a positive influence from the DAI Score on average wages.

Table 5: OLS Regression Results

Dependent variable: Log(Wages)
Heteroskedasticity-robust standard errors in parentheses, variant HC0

	Model 1	Model 2	Model 3	Model 4
Constant	6.0566*** (0.160)	6.0829*** (0.764)	5.9212*** (0.641)	2.1822*** (0.533)
Adjusted DAI	0.0170*** (0.003)	0.0111*** (0.003)	0.0075** (0.003)	0.0042* (0.002)
Regular Hours		0.0066* (0.003)	0.0058*** (0.003)	0.0101*** (0.002)
Extra Hours		0.0079 (0.009)	0.0238*** (0.006)	−0.0093* (0.005)
Employee Tenure		0.0852*** (0.013)	0.0671*** (0.012)	−0.0049 (0.012)
Employee Age		−0.0333** (0.014)	−0.0243** (0.011)	0.0290*** (0.009)
% of Bachelor's			0.0090*** (0.002)	0.0104*** (0.002)
Log (Gross Revenue)				0.1029*** (0.009)
R^2	0.33004	0.71321	0.787	0.853
Adjusted R^2	0.30974	0.66376	0.741	0.814

*** p<0.01, ** p<0.05, * p<0.1

Observing the Table 5 results, there seems to be statistical significance in supporting Hypothesis 1. Based on the results from the first Model which does not consider any control variables, an increase of 1 Adjusted DAI point in a given firm leads to an estimated increase of 1.7% in the average salary paid to its workers (p-value <0.0001), *ceteris paribus*. This result remains statistically significant with the addition of the selected control variables for hours worked, employee tenure and age in Model 2 (p-value=0.0001). Moreover, in Models 3 and 4, with the addition of the strongest variables, education and Gross revenue (the latter also working as a proxy for firm size) respectively, the Adjusted DAI loses some statistical significance and magnitude but still manages to uphold a p-value of 0.0546, remaining significant for an α of 0.10 and having a predicted increase on wages of 0.423% for each DAI point gained.

5 Discussion

This project aimed, firstly, to provide a starting analysis to the results of the digital maturity survey Digital Acceleration Index, developed by Boston Consulting Group and the first of its kind in Portugal. Secondly, it aimed to assess the relationship between the level of Digital Maturity and Wages within the Portuguese economy. Lastly, it looked to analyse trends digital maturity based on survey responses through a qualitative framework from text-based processing and data mining as an attempt at creating a machine based methodology to sift through big chunks of text.

The final sample of 797 firms in the DAI survey provided an average score of 40.79, slightly increased to 46.43 when adjusted for answers left in blank. This placed the Portuguese economy in a lower-intermediate level, classified as ”Digital Literate” by BCG's categorization. This result is in line with the findings from the European Comission (2020) which placed Portugal in a slightly below average position when compared to the European Union, mostly due to lagging behind in Human Capital digital skills. Responding companies were also asked for their expectations for improvement in the following two years and revealed a very optimistic outlook for such a short period, estimating an average increase of 16.5 DAI points, for a 2022 average expected score of 57.3. An analysis by firm size revealed that Medium and Big firms seem to have an advantage over Smaller ones. Separately, a sector analysis showcased a dominance of the ICT industry, while the Education sector proved to be the most confident in upgrading its digital maturity in the next few years. Lastly, a deeper dive into the results of different digital maturity topics present in the survey (here called blocks) did not show significant differences among them.

In regards to the model, the DAI stands out from the rest of practitioner models based on two traits. Firstly, due to its end to end range which encompasses the dimensions that are usually underrepresented in DMMs such as Business Model, Digital Ecosystems, Leadership, among others (Teichert, 2019). Secondly, the DAI differs from the majority due to its cyclical nature, given that it was designed to be repeated every 2 years and track the progress across each country where it is implemented. Moreover, one can argue that this is the first major practitioner DMM ever deployed in Portugal.

As mentioned before, the 2020 Digital Economy and Society Index from the European Comission, strongly points out the gap that Portugal still has in its Human Capital. In fact, Portugal's percentage of ICT graduates is only slightly above half of the European Average (1.9% and 3.6% respectively). With this skilled labor scarcity in mind, and after assessing the relationship between digitalization and productivity (Gal et al., 2019) it was hypothesized that a higher digital maturity can be a predictor for higher average salaries. The consequent multiple regression model revealed a statistically significant relationship between the two variables. In the first regression, the Adjusted DAI score without any control variables predicted an increase of 1.7% in gross wages for each Adjusted DAI point increase (p-value<0.0001). After controlling for variables such as education, employee experience and firm size, a unit increase in the Adjusted DAI score still has a positive and significant (α=0.10) (p-value = 0.0546) expected effect increase, albeit smaller (0.42%).

Finally, this project resulted in am important curated dataset, among the first of its kind, that will provide an important basis for future research done in the area of Digital Maturity.

Even though the DAI and the linear regression provided significant and interesting results, this project has some limitations that must be taken into account.

Regarding the data collection, since it was not perfectly identic for all firms, there are a few biases that might have come into play. Firstly, even though BCG and Nova School of Business and Economics catered to a small group of 44 responding companies by helping them fill out the survey correctly and ensuring that the right person or team in each firm was assigned the responsibility to answer, the remaining 1000 respondents were handled by the Instituto de Marketing Research and it is unlikely that such a big subset of firms had such a close walkthrough, if any at all. Naturally, this resulted in a higher rate of questions left unanswered, which not only harmed the quality of the data but also raises the question in certain cases as to whether the respondent was qualified enough to answer on behalf of his/her firm. Secondly, since it is a self assessment survey, there are psychological variants related to the employee appointed to respond, since some might be more optimistic/pessimistic in their expectations for the future and, in the case of high ranking managers, some might be averse to giving their own firm a bad rating or, in the case of bigger firms, might simply have a wrong perception of what really happens in the lower levels (Buvat et al., 2017).

As for the merging with the Workforce data and the consequent multiple regression model, perhaps the most significant caveat is the fact that despite the significant results between the Adjusted DAI score and Wages, an unilateral causal relationship can not be confirmed with full certainty. Effectively, one can argue that since improvements in digital maturity have been associated with increases in productivity, it should consequently lead to a higher average salary. However, one could also make the case in the opposite direction: a firm that is actively recruiting highly qualified employees, which tend to have higher salaries, will be more ready and advance more rapidly in digital transformation. Additionally, in the regression model, sectorial representativity was not always guaranteed since some sectors had only a few observations (see Table 1) although one could argue that since all these cases were big firms, it is expected that the number of observations is low.

In future developments on this topic, especially if further iterations of the DAI in Portugal do materialize in 2022 and 2024, it would be highly valuable to include the progression of digital maturity across time and see if the relation with salaries remained as robust. Additionally, since this Maturity Model was developed before the Covid-19 pandemic's full impact, future repetitions of the survey could have specific fields about the agility and changes that the lockdown brought up.

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