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Is it worth the hype? Influence of artificial intelligence efforts on key financial company metrics

Keywords: Artificial Intelligence, company performance, company value.

J E L Classification: M15, O32, O33.

Abstract: Artificial Intelligence poses a consortium of multiple digital technologies able to perform tasks which were thought about that they can only be done by humans. To do so, it applies complex learning and decision-making processes based on analysis of structured and unstructured data. Currently, AI is assumed to have massive benefits in the areas of efficiency and performance of companies, although the impact on financial key performance indicators (KPI) is still unexplored. The underlying thesis of this research is that the financial impact of AI can already be seen in practice. The research question is whether there is an impact of company-driven AI efforts on financial KPI, like the return on assets (ROA) and the market capitalization.

To obtain the intended results, a theoretical and empirical analysis was chosen as particular approach. Firstly, the existing scientific research is examined regarding already measurable financial impacts of digital technologies. In a second step, a regression model for panel data will be applied on a dataset containing financial data of the forty biggest German companies and their respective AI effort per year as a binary variable over a time period of seven years.

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As a result, a financial influence of AI cannot be verified yet on a statistically significant level. Despite of this, an increasing number of AI efforts over the last years can be confirmed.

Introduction

Recently, interest in Artificial Intelligence (AI) technologies has grown tremendously. One can observe this by discovering a steady occurrence in mainstream media and news and by recognizing a rising number of scientific publications concerning AI. While such technologies already accompany private persons through their daily lives in the form of voice assistants and intelligent smart home technologies, also companies are increasingly leveraging the enormous potential of such technologies (Collins, Dennehy, Conboy & Mikalef, 2021).

Although there is currently a lack of a general definition of AI as this research terminus is under constant development, there are multiple criteria determining the core elements of it (Wang, 2019).

In general, AI uses complex algorithms that are enabled by machine learning processes to perform tasks traditionally performed by humans. Artificial machines are considered intelligent if these tasks require some form of former human intelligence. This implies the ability to make independent decisions in non-trivial situations with complex interrelationships (Akter, 2022). Therefore, the independence and autonomy of decision making from predefined parameters pose the biggest difference to other, non-intelligent digital technologies.

Furthermore, Berente, Gu, Recker and Santhanam define AI as not only a single or a compound of various technologies, but as a generalistic designation for all computational advancements which push the frontier of enabling machines to solve even more complex problems and to handle even more difficult issues (2021). This evolutionary process transforms the whole field of information technology and is assumed to bring massive performance and efficiency gains for AI utilizing companies (Berente et al., 2021).

Due to the multiple applications of AI, these intelligent systems are considered as a disruptive innovation that has the potential to gain a competitive advantage and to transform value creation in a sustainable way (Reim, Åström & Eriksson, 2020).

Problem formulation and research methodology

Despite of all these assumptions and predictions from numerous publishers that AI will bring efficiency gains and monetary benefits, there is a lack of scientific verification of this forecast. The reason for this is that there is currently no scientific study that quantitatively examines the financial impact of AI on key metrics of companies. Consequently, it is not known whether AI activities have a positive or negative impact and whether the investment in such technologies pays off. It is also not known whether AI efforts have any quantitatively measurable consequence on success metrics at all. Thus, there is a research gap in this scientific area.

Therefore, the underlying working hypothesis can be formulated: If a company takes actions in the area of AI, this will have a measurable influence on its key financial metrics.

This leads to the following research question: *Do AI efforts have an impact on key financial metrics of companies?*

In order to answer this question a particular approach was chosen:

Firstly, existing studies on the subject will be reviewed. This includes scientific papers on the impact of digital technologies as well as publications specifically focusing AI.

Secondly, a sample of companies will be analysed regarding their AI in the last years. Specifically, their annual reports between the years 2016 and 2022 will be examined for any hint that indicates an investment or measure in the context of AI. The data obtained in this way will then be compared with two major financial KPI of the companies within a regression analysis for longitudinal data, whereby the working hypothesis can be tested for verification. By doing so, two separate models were applied.

Empirical literature findings

One of the first findings regarding the impact of new IT technologies is the productivity paradox.

This states that the introduction of an IT technology initially leads to a reduction in productivity within the first few years, due to considerable implementation costs (Brynjolfsson & Hitt, 1996). In the case of new, digital technologies such as AI, this development is currently continuing on a macroeconomic level. For example, the productivity gains of the largest OECD member countries have been decreasing continuously for twenty years, which contradicts the anticipated efficiency gains from increasing digitization. The term used to describe this phenomenon is technological optimism (Brynjolfsson, Rock & Syverson, 2017).

In contrast, it has already been proven that the use of IT is positively reflected in corporate value, as measured by Tobin's Q. Thus, an investment in IT signals future potential to the market, which leads to a higher valuation (Bharadwaj, Bharadwaj & Konsynski, 1999). Due to this, performance and market capitalization must be analyzed separately.

This is also in line with a study by Chen and Srinivasan, which addresses the introduction of digital technologies in companies (2019). According to them, digitalization has a negative impact on the ROA. Despite this, these companies have a much higher market-to-book value (Chen & Srinivasan, 2019).

Another case study focusing on the impact of AI on business processes verifies that the use of AI in the redesign of an existing process can lead to an increase in performance. This is mainly due to automation. Further advantages on the process level are an increase in efficiency and higher information reliability (Wamba-Taguimdje, Wamba, Kamdjoug & Wanko, 2020).

A further study relates to the increased analysis capability of high data volumes in the Big Data environment through AI. Accordingly, an investment in technologies that are capable for automated processing of information may lead to a significant contribution to sustainably increasing corporate performance. Decisive factors here are the high initial costs of introducing such complex systems as AI and the human capital within the company (Tambe, 2014).

Furthermore, it has also already been proved that the technological and human Big Data capabilities of the company are positively related to the competitive advantage and financial performance of the company. Thus, according to Anwar, Khan and Shah, both qualitative variables correlate positively with this financial metric (2018).

In summary, the results clearly show that the effects of AI are viewed ambivalently. While some see a productivity gain, others predict productivity losses. The same applies to the impact on corporate performance and enterprise value. The literature analysis therefore indicates an impact, while not giving a clear view whether this impact is positive or negative.

Primary research findings

To obtain a reliable verification of the working hypothesis, a primary data analysis was conducted. To do so, a medium-term period of seven years was chosen, as this is when the strongest effects of AI are expected (Ammanath, Hupfer & Jarvis, 2020). For measuring the impact on key financial metrics, company performance and company value were identified as significant KPI.

The data basis contained the 40 largest German companies from 2016-2022. This guaranteed high diversity of different industrial sectors. The annual reports of the companies posed the source for the required information, as they contain all relevant financial figures and describe details of AI efforts that were planned or implemented in the respective fiscal year. These documents therefore contain all the necessary information needed for this investigation. Two companies were excluded due to a lack of data. The sample thus consists of 38 companies and 266 data sets.

AI effort was measured as a binary variable with the values 0 and 1 (0=no AI effort in this year; 1=AI effort in this year). The value was assigned according to whether there was a reference to possible AI activities in the report of the respective fiscal year. This was manually implemented by means of a linguistic analysis concerning the terms "AI" and "Artificial Intelligence" for each data set.

The dependent variables used were ROA to measure company performance and Tobin's Q to measure company value. ROA is most suitable for measuring performance because it not only looks at a company's profit, but also relates it to total assets, which allows different companies to be compared (Karahanna & Preston, 2013). Tobin's Q has been used to measure the value of a company because this ratio considers the perspective of the market in addition to the pure book value of the company (O'Reilly, Caldwell, Chatman & Doerr, 2014). In addition, the calculation components of the two dependent variables were added as control variables.

In a first step, the correlations between the variables were examined. The following scale was chosen as the significance level (p):

- $p<0.01$ highly significant
- $p<0.05$ significant
- $p<0.1$ lowly significant
- $p>0.1$ not significant

Table 1 presents the results in a correlation matrix based on the Pearson-Correlation coefficient.

Table 1. Correlation matrix

	FY	ROA	Tobins Q	AI effort	Net income	Total assets	Total equity	Market capitalization
FY	1	0.05	-0.04	0.28***	0.11*	0.03	0.12*	0.05
ROA	0.05	1	0.05	0.03	0.29***	-0.11*	0.01	0.09
Tobins Q	-0.04	0.05	1	-0.14**	-0.28***	-0.3***	-0.44***	-0.12**
AI effort	0.28***	0.03	-0.14**	1	0.23***	0.23***	0.38***	0.39***
Net income	0.11*	0.29***	-0.28***	0.23***	1	0.27***	0.72***	0.54***
Total assets	0.03	-0.11*	-0.3***	0.23***	0.27***	1	0.62***	0.24***
Total equity	0.12*	0.01	-0.44***	0.38***	0.72***	0.62***	1	0.57***
Market capitalization	0.05	0.09	-0.12**	0.39***	0.54***	0.24***	0.57***	1
*p<0.1; **p<0.05; ***p<0.01								

Source: own study.

As we can see, fiscal year (FY) is strongly positively correlated with AI effort ($p<0.0.1$), indicating that companies have increasingly undertaken AI activities in recent years. The correlation value is also relatively high at 0.28 in comparison to the other variables. Also, the number of companies undertaking AI efforts has increased rapidly over time within the sample. While in 2016 only 21% had AI on their agenda, the following year it was already 39%. In 2018, this proportion rose to 55%, where it stagnated in 2019 and rose again rapidly to 71% in 2020. After that, it reached its peak at 82% in 2021 and got back to the proportion two years ago with 68% in 2022.

Looking at the performance, no significant correlation with AI was found. The correlation strength is also very low with a value of 0.03. This situation is completely different for the company value indicator Tobin's Q. The correlation with AI effort is only slightly negative at -0.14, but significant. Among the variables to be investigated, Tobin's Q is the only KPI that can be verified as having a significant influence.

An examination of the control variables reveals highly significant correlations, which can be interpreted as extremely positive for the meaningfulness and quality of the statistics.

For further investigation of the sample, a regression analysis was performed following the identification of the individual regressions. This included two models:

- Model 1: Influence AI effort on performance KPI ROA
- Model 2: Influence AI effort on value KPI Tobin's Q

Table 2. Regression models

	Model 1	Model 2	
Dependent variable:	**ROA**	**Tobins Q**	
AI effort	0.001	0.025	
p-value	(0.871)	(0.797)	
Standard error	(0.006)	(0.096)	
Net income	0.00001***	0.00001	
p-value	(0.000)	(0.735)	
Standard error	(0.00000)	(0.00002)	
Total assets	0.000	0.000	
p-value	(0.966)	(0.503)	
Standard error	(0.00000)	(0.00000)	
Total equity	-0.00000***	-0.00002***	
p-value	(0.000)	(0.001)	
Standard error	(0.00000)	(0.00001)	
Market capitalization	0.00000	0.00001***	
p-value	(0.615)	(0.000)	
Standard error	0.000	0.000	
Constant	0.033***	1.735***	
p-value	(0.001)	(0.000)	
Standard error	(0.010)	(0.189)	
Observations	263	263	
R2	0.335	0.108	
Adjusted R2	0.322	0.091	
F Statistic	130.220***	29.700***	(df = 5)
Note:	*p<0.1	**p<0.05	***p<0.01

Source: own study.

Since the data are longitudinal with strong interdependencies, heteroscedasticity and autocorrelation had to be tested (Liang & Zeger, 1986). As estimators, a random effects estimator and a fixed effects estimator were used. Which one of the two applied, was identified by using a Hausman test based on a significance level of 5% (Greene, 2002). The homoscedasticity required for this was checked using a Breusch-Pagan test (Breusch & Pagan, 1979). Additionally, since heteroscedasticity was present in both models, a heteroscedasticity-consistent estimator was applied that transformed the standard errors to robust standard errors.

For this purpose, the sandwich package for R by Zeileis was applied, which was developed specifically for such statistical problems (Zeileis, 2004). Finally, the Durbin-Watson test was used for checking for autocorrelation (Greene, 2002). If there was an issue with autocorrelation in the model, an autocorrelation-consistent estimator was added (Zeileis, 2004).

Doing so, two models were generated examining the regressions of the independent variable AI effort on the target variables ROA and Tobin's Q. Figure 2 shows the results.

The F-statistics of both models are highly significant, which allows a transfer of the findings from the sample to practice. The adjusted R^2 is 0.322 for Model 1 and 0.091for Model 2. The adjusted R^2 is significantly lower than the R^2 due to the relatively small sample size. A random-effects estimator was used for both models based on the results of the Hausmann test.

Model 1 shows whether there is a regression between AI effort and ROA. This cannot be confirmed applying the predefined significance scale. The p-value of AI effort in this model is 0.871 and the corrected standard error is 0.006. The marginal positive effect on company performance of 0.001 is thus not significant.

Model 2 shows whether there is a regression between AI effort and Tobin's Q. Again, no significant effect can be found at a significance level of $p<0.1$. The p-value of AI effort here is 0.797 and the corrected standard error is 0.096, which poses a slightly higher significance than Model 1, but far from a verified result. Within the sample, there is thus a weak, positive influence of AI effort on the company value amounting to 0.025.

Discussion and conclusions

Based on the macroeconomic literature, no influence of AI can be detected. For example, productivity growth rates in all economies have been declining significantly for years, despite an rising trend predicted by technological optimism.

An reversal of this due to the increasing spread and potential use of AI is not expected in the short term (Brynjolfsson et al., 2017). At the company level, the situation is much less distinct. The existing study results are extremely ambivalent with regard to the effect of AI. Some researchers assume a performance gain here, which is achieved through cost reductions and efficiency increases on process level (Wamba-Taguimdje et al., 2020). The core here is that solely acquiring an AI technology is not sufficient to increase business performance. Rather, embedding the technology into the company structure and business model is essential. Only in this way, the potential of AI can be exploited profitably. This is also significantly determined by the available human capital, which has a positive influence on financial performance if appropriate skills regarding digital technologies are within the company (Anwar et al., 2018).

In contrast, other studies indicate a clear negative impact on performance. This is mainly due to the high initial costs in the first year, including the initial investment and the training of the employees (Tambe, 2014). This has a negative impact on the ROA, especially in the first year of implementation (Chen & Srinivasan, 2019).

The paradox of productivity can be also applied to AI. However, two points should be noted: First, this concept was originally developed for the introduction of nowadays basic IT infrastructure. The principle therefore mainly refers to the initial introduction of an IT system if there was no IT in the company before. In the meantime, it can be assumed that every company has at least a minimum of IT infrastructure that can be used as a basis for the introduction of AI. The starting situation therefore differs from that when this theory first emerged (Brynjolfsson & Hitt, 1996). Whether this principle is applicable in an unchanged way to emerging AI should thus be questioned. Second, scientific studies mostly refer to digital technologies as a whole and do not narrow their focus to a single, specific technology like AI. The extent to which this affects the outcome with respect to AI remains also unclear.

The primary data analysis conducted as part of this research cannot contribute to clarify this question. The impact of AI effort on the performance KPI is not significant. This applies to the correlation as to the regression.

By looking at the value KPI, we can observe much more distinct assumptions, even though far less research has been conducted in this area. For instance, according to existing literature, IT efforts have led to a higher valuation of enterprise value as measured by Tobin's Q. This is due to the apparent future orientation of the company (Bharadwaj et al., 1999). A more recent study analogously assumes that this also applies to the increasing application of digital technologies, which also includes the usage of AI (Chen & Srinivasan, 2019). The market therefore rewards AI activities with a higher valuation.

To verify this, the sample has to be analysed. Limiting to the regression between AI effort and Tobin's Q, no practical conclusion can be drawn. Within the analysis, AI has a very weak positive effect on enterprise value but lacking any significance. However, these two variables correlate slightly with each other with a negative strength of -0.14, which is in contrast with the results of the literature analysis. Focusing on the primary findings, AI activities and the company market value have a negative impact on each other. However, it should be noted that this is only true for the bivariate correlation. By including other influencing variables within the regression, the effect of AI effort cannot be generally confirmed for practice. Nevertheless, the negative correlation is significant, which leads to the fact that the statement of the thematizing literature cannot be verified.

For these reasons, the working hypothesis must be rejected. It cannot be clearly decided whether AI activities impact key financial metrics like company performance or value.

Apart from this, the fiscal year correlates strongly positively with AI effort, which means that companies are conducting more and more projects in the field of AI. This confirms the increase in interest in the technology and explains the current high level of investment and public attention.

It should also be noted that there is currently still little monetary research on the effects of AI and that the primary data of this research is limited to German companies. Future research should therefore broaden its view to an international sample and should consider a longer time period. The analysis should also be carried out again in the future, as more data will be available with the chance of higher validity of the results. A more differentiated research approach could be realized, if level of AI activity could be quantified instead of using a binary variable indicating ‘yes’ or ‘no’.

It should also be noted that only big companies were analysed. Future studies should therefore also focus on small- and medium-sized enterprises to take local and national companies into account. In addition to that, a separated analysis for different industrial sectors would be senseful, as the AI expenditures may vary between industries.

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