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Artificial Intelligence: a multi-purpose term

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1 Interdisciplinary perspective of AI 268

2 Survey results: Economic Consequences of AI 269

3 Summary 272

4 References 273

Abstract:

Artificial Intelligence (AI) is used as a multi-purpose term. Survey data shows that expectations on the economic consequences of AI are less consistent than they might be. Therefore economic policy should focus on specific categories of AI rather than AI in general.

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1 Interdisciplinary perspective of AI

The use of the term Artificial Intelligence (AI) follows an evolving concept, which adapts to the technological frontier: Leonardo da Vinci designed a humanoid "robot" around 1495 that looks like a medieval knight (Nilsson, 2010, p.1). The mathematical and computational work for AI started in the 1950s. A chess computer defeated world champion Garry Kasparov in 1996. But this outstanding artificial intelligence is outdated twenty years later. Nilsson presents a detailed overview on the historical development (Nilsson, 2010).

Most recently, Artificial Intelligence is used as a multi-purpose term, e.g. describing

- Problem solving, for example search and planning processes
- Data analytics and pattern recognition, also of unstructured data
- Machine learning
- Predictions

in the fields of

- Production technology
- Mobility (e.g. autonomous driving)
- Security (e.g. video tracking) and military applications
- Private services (e.g. health, translations)
- Business administration (e.g. controlling, trade)

and many more. The scope of research ranges from specific and local applications, e.g. in a cleaning robot at home, up to broader and fully connected systems to attain AGI (artificial general intelligence) or HLMI (human level machine intelligence). Also the mathematical methods behind are changing, depending on calculating power and software development. Neural networks are only one of the many methods that can be applied in an AI context (for an overview see a standard textbook such as Russell and Norvig, 2016). In this volume Meisen, Meyes and Tercan compare four different machine learning models to predict the geometry deviation of windshields in automobile production (Meisen et al, 2019).

At the same time, physicists and philosophers point out the long-term consequences as decisions are delegated from humans to artificial intelligence systems that begin to tackle human domains of emotional intelligence and creativity.

Taking into account the most recent developments Artificial Intelligence is now being intensively discussed in the field of politics regarding:

- Ethical standards
- Data security and protection
- Industrial policy (e.g. AI initiatives)

- Distribution of income
- Education

The approaches are manifold, as a comparison of national AI strategies shows (see Groth at al., 2018) and to gain an idea of the long-term economic consequences of AI for industrial production a survey was carried out.

2 Survey results: Economic Consequences of AI

2.1 Database

During Automatica 2018, which took place in Munich in June 2018 and announces itself as "the leading exhibition for smart automation and robotics" (see https://automatica-munich.com), students from the University of Applied Sciences Ruhr West, Mülheim a. d. R., Germany, interviewed 49 visitors and exhibitors about their assessment of Artificial Intelligence. The questionnaire had 14 questions, most of them with ordinal options given. Four student teams asked for expert interviews in different halls of Automatica. The interviewees were selected randomly, i.e. by chance. After sorting out incomplete questionnaires, answers from 36 participants were used for the analysis.

2.2 Mean assessments

The analysis reveals unanimous and not unanimous assessments. Defining that an assessment is unanimous when the answer with the second largest frequency is next to the answer with the maximum frequency on the ordinal scale. Otherwise the assessment is said to be not unanimous.

The following barplot shows the distribution of observations related to the question whether AI leads to an increase of unemployment globally in the next five years. The distribution is symmetric and bimodal. Roughly 40% of the participants are optimistic and 40% are pessimistic about the total labor market effects of artificial intelligence. Therefore the assessment is not unanimous according to the definition mentioned above.

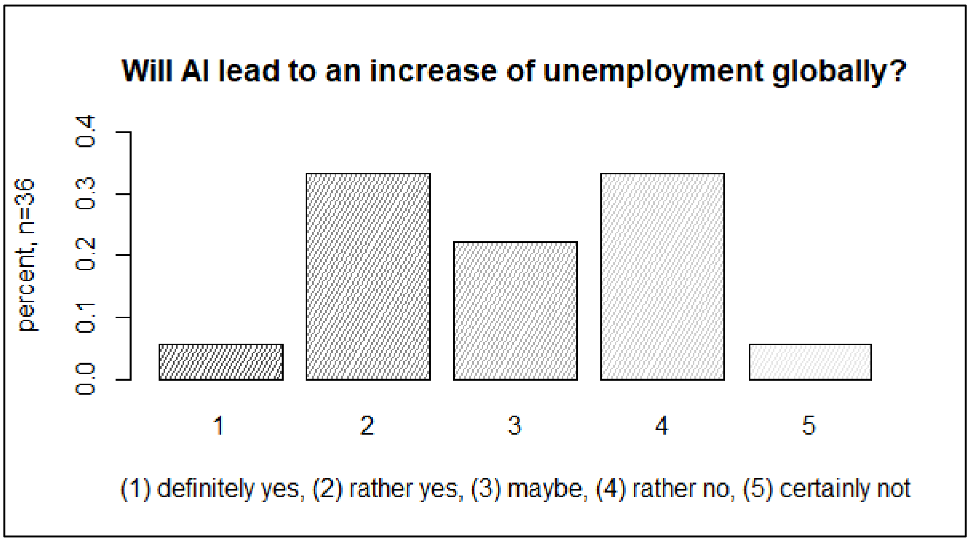

Figure 1: Survey result: AI and unemployment

Using this simple definition, the following assessments show an unanimous pattern:

- The majority of participants (58%) believes that self-learning and automatically optimizing machines will be an industry standard in 2023.
- 67% of the participants believe that AI will lead to a strong or medium individualization of products in the next five years.
- 72% expect that there will be higher average wages in industry.

Not unanimous assessments result here:

- A majority (62%) expects decreasing unit costs in production, but a minority (23%) predicts a slight or medium-sized increase of unit costs.
- Roughly half of the participants (53%) expects an increase in concentration in industrial production (fewer manufactures), but a minority (34%) believes that competition will become stronger in the next five years.
- Also half of the participants (53%) guess that only a few countries will benefit. A minority predicts that all countries will benefit.
- 40% of the participants believe that unemployment will increase, and another 40% expect a decrease (see barplot above).

A comparison of the unanimous and not unanimous assessments leads to the presumption that effects on a macroeconomic level are much more difficult to predict than changes in production technology.

2.3 Correlations

A consistent answering behavior should result in high correlation coefficients regarding the items which are economically interdependent. Overall, the coefficients of correlation are small. The absolute numbers are in a range between 0 und 0.33, using both, the methods of Kendall and Spearman.

An example: 39% of the participants believe that AI will lead to a strongly or modestly higher concentration of good producers. But, only half of the 39% expect that there will be also a strong or modest effect on country level, i.e. a few countries benefiting more than others do. The coefficient of correlation between the two items amounts to -0.19. The participants on average have no consistent view on the consequences of AI regarding competition and country specific advantages.

The following picture provide a visual interpretation of a combination of two items which indicates that there might be a weak consistence with at least two items: The left bar represents the participants which expect a strong or modest individualization of products in the next five years. The right bar reflects the number of participants which believe in a strong or modest standardization of products. The upper bar shows how many participants expect higher unemployment (definitely or rather yes) and the lower bar represents the expectation that unemployment will not increase due to AI (rather or certainly not). The cell in the lower left corner represents the optimistic participants who expect more individualization and no increase in unemployment. This cell (only) accounts for 25% of the total plot, e.g. of the participants. The effect would even vanish if the answering options were not merged and the mosaic plot

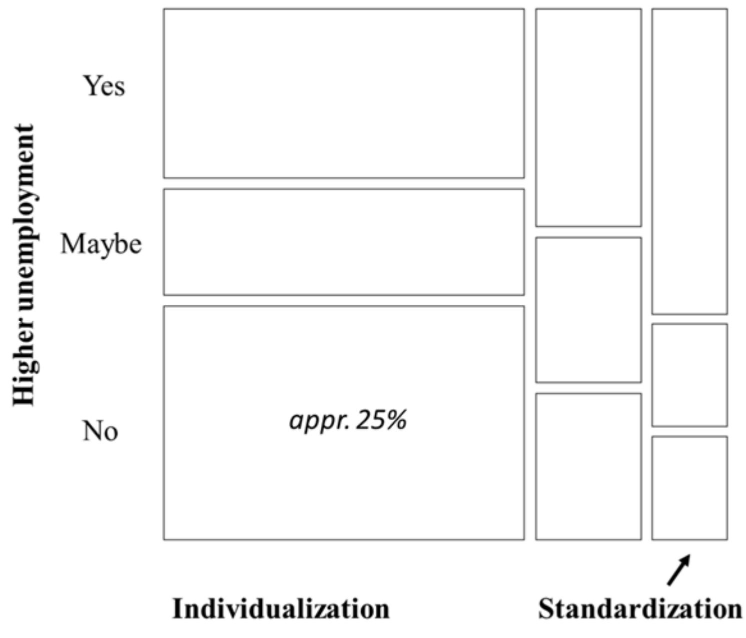

Figure 2: Mosaicplot: Individualization of products vs unemployment

built up on the original scale with 7 options. Kendall's coefficient of correlation amounts to -0.18 then. This also shows the shortcomings of the analysis because the level of aggregation influences the results.

2.4 Time lime predictions

The participants were also asked, whether AI at some point will be able to manage and to lead companies by their own more successful than human managers. The majority (77%) believes that this never will be the case. The others participants were asked to predict when this point will be reached. The estimations vary between 5 and 100 years. Due to the low total number of participants this result should not be interpreted further, but it confirms the results of time line studies that there is a large variability in the predictions (see Armstrong and Sotala (2015); Müller and Bostrom (2016); Grace et al. (2018); an overview is also presented by the webpage https://aiimpacts.org[1]).

2.5 Interpretation

AI creates predictions, but is not predictable itself. On average, assessments about the economic consequences of AI are not unanimous and not consistent. This may be caused by the multi-purpose use of the term AI, a not specific enough questionnaire, or the general problem of too many different drivers influencing the real economic development.

Also political recommendations may depend on one's individual definition of AI, perspective and experience. If this is true, economic policy has to focus on specific categories of AI rather than on AI in general.

3 Summary

This short paper provides an overview on the multi-purpose use of the term Artificial Intelligence and presents empirical results of a survey conducted during the Automatica 2018. It concludes that the multi-purpose use of the term is one reason for the not unanimous assessment of the economic consequences of AI on average. If this is true, economic policy has to focus on specific categories of AI rather than on AI in general.

[1] https://aiimpacts.org/category/ai-timelines/predictions-of-human-level-ai-timelines/ai-timeline-surveys, last access: February 2019

4 References

Armstrong, St.; Sotala, K. (2015): How We're Predicting AI – or Failing to. In: Romportl, J.; Zackova, E.; Kelemen, J.: Beyond Artificial Intelligence - The Disappearing Human-Machine Divide. Springer, Berlin. pp. 11-29.

Grace, K.; Salvatier, J.; Dafoe, A.; Zhang, B.; Evans, O. (2018): When Will AI Exceed Human Performance? Evidence from AI Experts. Working Paper. Last access Febr. 2019, https://arxiv.org/pdf/1705.08807.pdf; arXiv:1705.08807v3.

Groth, O.; Nitzberg, M.; Zehr, D.; Straube, T.; Kaatz-Dubberke, T. (2018): Vergleich nationaler Strategien zur Förderung von Künstlicher Intelligenz, Teil 1. Konrad-Adenauer-Stiftung. Last access Febr. 2019, https://www.kas.de/einzeltitel/-/content/vergleich-nationaler-strategien-zur-forderung-von-kunstlicher-intelligenz

Nilsson, N. J. (2010): The Quest for Artificial Intelligence, Cambridge University Press, New York, USA.

Meisen, T; Meyes, R.; Tercan, H. (2019), Artificial Intelligence in Automotive Production, in: Mobility in a Globalized World, Conference Volume, forthcoming.

Müller, V. C.; Bostrom, N. (2016): Future progress in artificial intelligence: A Survey of Expert Opinion. In: Vincent C. Müller (ed.), Fundamental Issues of Artificial Intelligence, p. 553-571. Springer, Berlin. Last access to online resource Febr. 2019, https://nickbostrom.com/papers/survey.pdf

Russell, St; Norvig, P. (2016): Artificial Intelligence – a modern approach. 3rd edition. Pearson, Harlow.