



# Technequality

Understanding the relation between technological innovations and social inequality

**Labour market forecasting scenarios for automation risks and the impact of artificial Intelligence on productivity**

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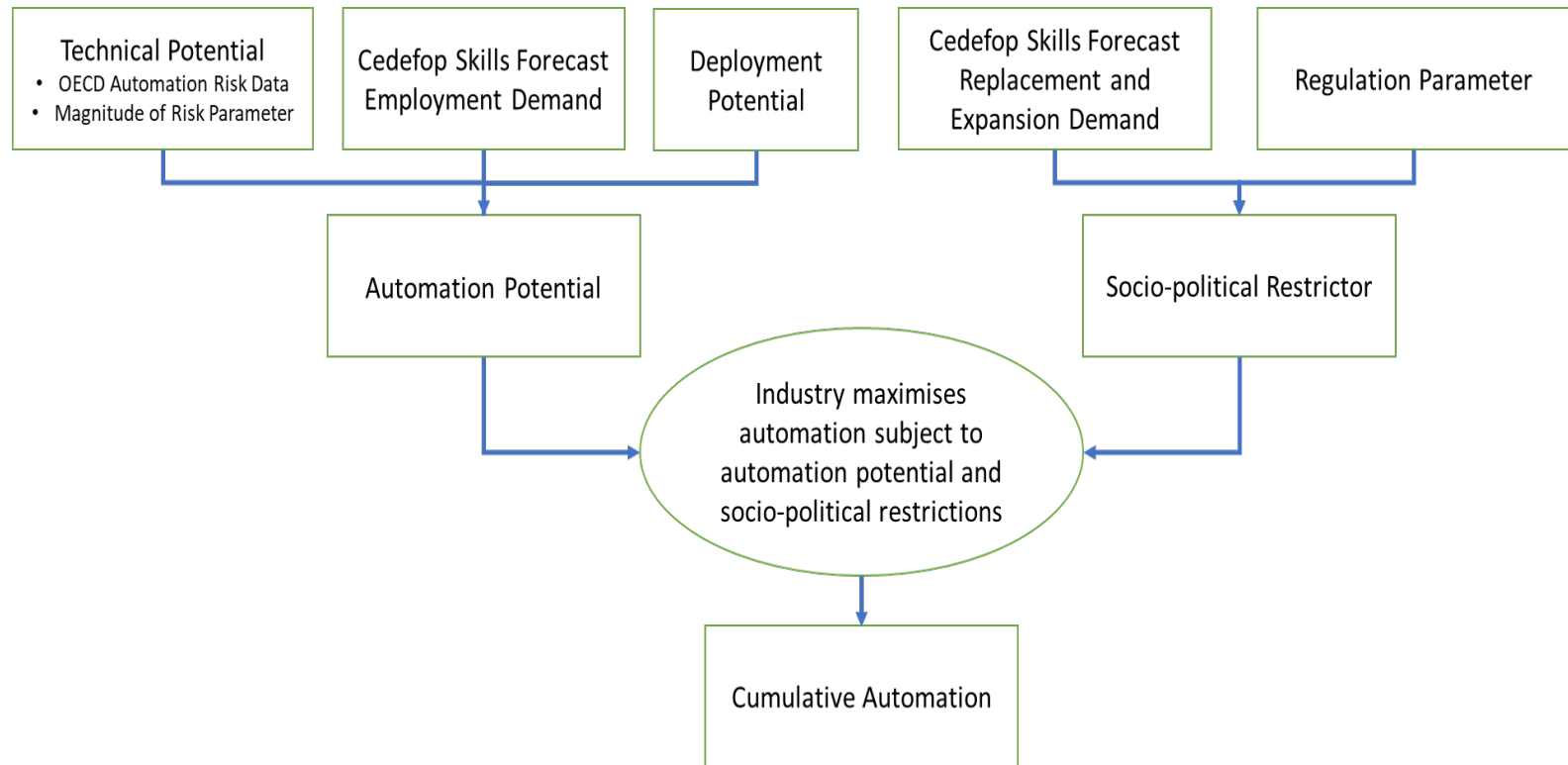


# Outline

- **Labour market forecasting scenarios for automation risks**
  - Model of automation
  - Scenario assumptions
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  - Policy recommendations
- **Artificial intelligence and productivity**
  - Research /experiment
  - Results
  - Policy recommendations

# Labour market forecasting scenarios for automation risks

## *Model of automation*



# Labour market forecasting scenarios for automation risks

## *Scenario assumptions*

Parameter	Description	Assumptions
Automation risk (Technical potential)	OECD automation risk by occupation (three categories: high (>70%), significant (50-70%), and low (<50%)).	Low: lower bound in range
		Middle: mid-point of range
		High: upper bound in range
Speed of adoption of automating technologies	The year in which full technical potential could be realised.	2035
		2055
		2075
Economic and socio-political barriers	Restriction on automation.	No employment protection
		Employment protection.

# Main scenario results

*(% difference from Cedefop Skills forecast 2018 by 2030 in EU-28):*

<https://www.camecon.com/tools/labour-market-forecasting/>

	No employment protection			Employment protection		
	2035	2055	2075	2035	2055	2075
High	44%	20%	13%	37%	19%	12%
Middle	31%	14%	9%	28%	13%	9%
Low	18%	8%	5%	17%	8%	5%

# Labour market forecasting scenarios for automation risks

## *Recommendations for policy responses*

- Flexibility and adaptability
- Preparedness
- Moderated transitions
- Target solutions
- Alertness to unintended consequences

# Automation > Artificial intelligence: A new threat?

Science

RESEARCH ARTICLES

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10.1126/science.1251733 (2017).

## Superhuman AI for heads-up no-limit poker: Libratus beats top professionals

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No-limit Texas hold'em is the most popular form of poker. Despite AI successes in perfect-information games, the private information and massive game tree have made no-limit poker difficult to tackle. We present Libratus, an AI that, in a 120,000-hand competition, defeated four top human specialist professionals in heads-up no-limit Texas hold'em, the leading benchmark and long-standing challenge problem in imperfect-information game solving. Our game-theoretic approach features application-independent techniques: an algorithm for computing a blueprint for the overall strategy, an algorithm that fleshes out the details of the strategy for subgames that are reached during play, and a self-improver algorithm that fixes potential weaknesses that opponents have identified in the blueprint strategy.

In recent years the field of artificial intelligence (AI) has advanced considerably. The measure of this progress has, in many cases, been marked by performance against humans in benchmark games. AI programs have defeated top humans in checkers (1), chess (2), and Go (3). In these perfect-information games both players know the exact state of the game at every point. In contrast, in imperfect-information games, some information about the state of the game is hidden from a player—for example, the opponent may hold hidden cards. Hidden information is ubiquitous in real-world strategic interactions, such as business strategy, negotiation, strategic pricing, finance, cybersecurity, and military applications, which makes research on general-purpose techniques for imperfect-information games particularly important.

Hidden information makes a game far more complex for a number of reasons. Rather than simply search for an optimal sequence of actions, an AI for imperfect-information games must determine how to balance actions appropriately, so that the opponent never finds out too much about the private information the AI has. For example, bluffing is a necessary feature in any competitive poker strategy, but bluffing all the time would be a bad strategy. In other words, the value of an action depends on the probability it is played.

Another key challenge is that different parts of the game cannot be considered in isolation; the optimal strategy for a given situation may depend on the strategy that would be played in situations that have not occurred (4). As a conse-

quence, the heads-up (that is, two-player) variant prevents opponent collusion and kingmaker scenarios where a bad player causes a mediocre player to shine, and therefore allows a clear winner to be determined. Due to its large size and strategic complexity, heads-up no-limit Texas hold'em (HUNL) has been the primary benchmark and challenge problem for imperfect-information game solving for several years. No prior AI has defeated top human players in this game.

In this paper we introduce Libratus, (22) an AI that takes a distinct approach to addressing imperfect-information games. In a 20-day, 120,000-hand competition featuring a \$200,000 prize pool, it defeated top human professionals in HUNL. The techniques in Libratus do not use expert domain knowledge or human data and are not specific to poker; thus they apply to a host of imperfect-information games.

### Game-solving approach in Libratus

Libratus features three main modules:

(i) The first module computes an abstraction of the game, which is smaller and easier to solve, and then computes game-theoretic strategies for the abstraction. The solution to this abstraction provides a detailed strategy for the early rounds of the game, but only an approximation for how to play in the more numerous later parts of the game. We refer to the solution of the abstraction as the blueprint strategy.

(ii) When a later part of the game is reached during play,

"Current AI techniques  
are at or above the  
numeracy and literacy  
proficiency of 89% of  
adults in OECD  
countries."

Source: Elliott, S.W. (2017), *Computers and the Future of Skill Demand*,  
OECD Publishing, Paris

# But AI still needs to be supported by employees in the near future

## *Our research*

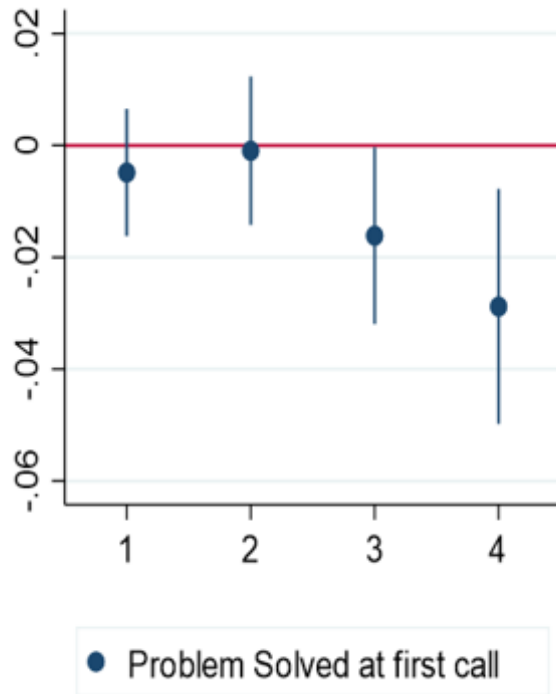
- Insider econometrics in combination with field experiment
- Exploiting micro data to study the causal effects of AI-based automation on workers' performance
- Field Experiment in multi-national telecommunication company in 2019/2020: Service centre unit for private customers
- Subject of our research: customer advisors



# AI Experiment set up

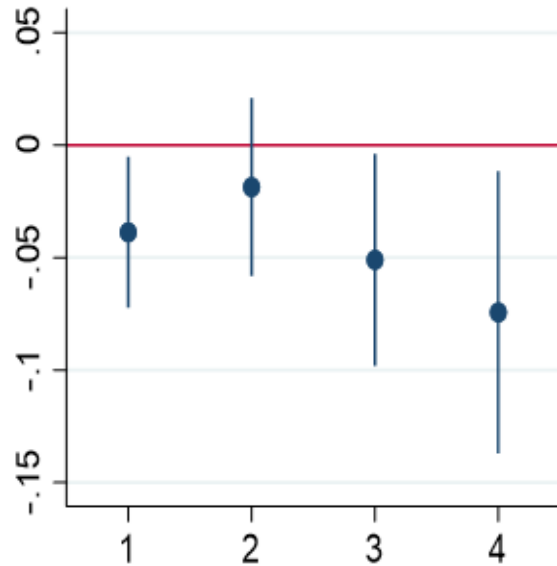
- **Randomized introduction** of RDA (AI) in the form of a personal interactive assistant: enabling treatment and control groups
- System interacts with worker during customer calls
- **Goal of RDA implementation:** Better service, less mistakes, reduction of multiple calls for same issue & more pleasant work situation for agents
- **Four basic functions:**
  - automation of routine tasks
  - information retrieval
  - calling up of second systems (interface)
  - reminder of work steps and process-oriented guidance

# Results of AI introduction



- Drop in productivity
  - Not caused by demotivation of employees
  - Or that the AI is corrupted

# Distraction and too heavy reliance on AI by employees



- Drop in productivity
  - Becomes bigger with the number of AI applications available
  - Personal effort perceived by customers declines

# Summarized by Little Britain



# AI experiment conclusions

## *Recommendations for policy responses*

- Flexibility and adaptability
- Preparedness
- Alertness to unintended consequences

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