ANALYSIS PLAN FOR "BELIEFS AND ATTITUDES ON AUTOMATION AND AI"

Hypothesis

Part 1: misperceptions/beliefs on automation and AI

A first set of hypotheses concerns misperceptions of the effects of automation and AI on the labour market:

- H1: there will be widespread misperceptions over automation and AI. Some of this will be out of ignorance and will lead to random answers, some will be systematic.
- H2: there will be some polarization over the impact of automation and AI, with many respondents potentially overestimating the positive impact of automation and AI on the labour market and many respondents doing the opposite.
- H3: the larger the misperceptions, the larger the extent of the over(under)estimation of the impact of automation and AI on the labour market.

A second set of hypotheses deals with the determinants of misperceptions on automation and AI. More specifically, we will look at exposure to AI, exposure to automation (instrumented), cultural worldviews, and political orientation.

Exposure to automation may impact misperceptions through two different channels. On the one hand, exposed individuals may be more negative about automation and AI because they feel their job is being threatened. On the other, they may have more information on the actual impact of automation and AI.

- H4a: exposure to automation and AI increases the overestimation of the negative impact of automation and AI.
- H4b: exposure to automation and AI increases the precision in the estimates.

Cultural worldviews may matter as well. Individuals who dream about a mythical "golden age" of the past, or more in general who refuse post-modernism, may be more inclined to opposition to technological change.

- H5: individuals whose cultural views are less liberal overestimate the negative impact of automation and AI more than liberal ones.

Finally, there may be a role for political orientation. It is well known that supporters of extreme parties are more prone to believing conspiracy theories and that they see potential threats. Furthermore, as voters of these parties usually associate technological change to the techno-optimistic elites they tend to despise, they may intuitively react against innovation. This might be true more generally of voters on the left of the political spectrum, who might be more concerned about the distributional effects of technological change.

- H6: prospective extreme parties voters overestimate the negative impact of automation and AI more than mainstream parties voters .
- H6a: prospective leftist voters overestimate the negative impact of automation and AI more than other voters

We will also consider a number of additional individual characteristics, including age, gender, living area, religion, income, education, occupation, field of study, use of technology in daily life and feelings towards technology. At the end of this part, we will have open questions on the respondent's opinion on the impact of automation and AI on the labour market. This will be used as further outcome variable to assess H1-H6 and, together with the beliefs, to assess how opinions change after reading the visions in Part 2.

Part 2: political visions on technology, policies and political mobilization

Policy preferences:

A first set of hypotheses is related to policy preferences and comes from between-subject comparisons, under the assumption that these statements will persuade participants of their arguments, either genuinely changing their preferences or providing a rationale for expressing those opinions.

- H7: The techno-optimistic vision will lead individuals to be more in favor of un-targeted innovation.
- H8: the techno-pessimistic vision will lead individuals to favor un-targeted barriers to automation and AI and generalized redistribution policies.
- H9: the balanced vision will lead individuals to favor all kinds of policies more.

Our next hypothesis deals with how individuals would react depending on their political orientation.

- H10: The techno-optimistic vision will also lead individuals to be more in favor of redistribution, but only if the individuals' political orientation is left-wing. The opposite for the techno-pessimistic vision.

Our next hypothesis deals with how individuals would react depending on their prior misperceptions and opinions. This is the within-subject component of our empirical tests. We expect here that the vision reinforces the policy preferences naturally associated to prior beliefs. In other words, we expect confirmation bias to be the main psychological driver of the visions' influence. An alternative hypothesis is that misperceptions are related to uncertainty rather than to prior beliefs. In this sense, we would be capturing, with misperceptions, true ignorance on the phenomenon of automation and AI. If this is the case, then visions could persuade individuals that technological change is good/bad, and we would then see a difference between prior beliefs and ex-post policy preferences.

- H11a: Individuals will be more strongly influenced by the visions in the direction posited by H7, H8 and H9 if their misperceptions are aligned with the vision, that is if those who overestimate the negative impact of automation and AI are confronted with the techno-pessimist vision or if those who underestimate it are confronted with the techno-optimistic vision. Therefore, these visions will increase polarization over the topic.
- H11b: Individuals will be more strongly influenced by the visions in the direction posited by H7, H8 and H9 the larger their misperceptions regardless of their direction. In that case, H8 will come out as the strongest influence on policy preferences.

As with misperceptions, exposure to automation may both undermine or enhance the impact of visions. Exposure to automation may impact misperceptions through two different channels. On the one hand, exposed individuals may be more “techno-pessimist” or “balanced” themselves, so that that those visions provide a rationale for their doubts in the spirit of Bursztyn et al. (2020) or they may be less affected by visions in the first place because they already have a strong well-defined opinion on the topic.

- H12a: exposure to automation and AI increases the influence of the “techno-pessimist” and “balanced” visions.

- H12b: exposure to automation and AI reduces the influence of visions.

We will also test if, independently of the political statements, individual characteristics such as gender, age, education, living area, exposure to automation, occupation and political orientation have an influence on these AI- and automation-related policy preferences. More specifically, we will be concerned with how political orientation, occupation and exposure to automation may lead to different policy preferences regarding breaking up big tech, i.e. a policy to reduce market concentration.

Political mobilization:

An additional set of hypotheses deals with the willingness of individuals to mobilize on these topics. In fact, it is still unclear how much individuals would be willing to make the issue of technological change a cornerstone of their political identity much in the same way as they did with redistribution, welfare, discrimination, gender and immigration in the recent past. An argument from Gallego and Kurer (2022) is, indeed, that they deflect this issue on other topics exactly because technological change does not create enough identity for the time being. We will provide evidence on this by looking at the share of individuals who are willing to sign an online petition created by us related to the statements at Change.org.

There is limited evidence so far on these mechanisms. As for policy preferences, some hypothesis will come from between-subjects comparisons, others from within-subject ones. The first hypothesis relates to the willingness to mobilize on this topic which, based on previous studies, should be low. However, we posit that, consistently with prospect theory (Kahneman and Tversky, 1973), the prospect of negative consequences will push people to mobilize more than the prospect of positive ones:

- H13: mobilization will be very low regardless of the political statement.

- H14: mobilization in support of or in opposition to the statement will be higher for individuals who have seen the techno-pessimist narrative than the techno-optimistic one.

We will then look at how much people are willing to mobilize depending on their prior beliefs on automation/AI and depending on individual exposure to automation, cultural worldviews and political orientation. Another hypothesis related to prior beliefs come from social categorization theory (Turner et al., 1987), i.e. the higher the distance between the own preferences and the opposite narrative, the higher the chances of building up an identity, the lower the distance, again the higher the chances.

- H15: we will see polarization on mobilization. The probability of mobilizing will be increasing in people’s intensity of their pre-statements’ pessimistic or optimistic views of the phenomenon.

A separate hypothesis comes from considering misperceptions. On the one hand, misperceptions may mirror an underlying polarization, on the other they may make people more inclined to follow the lead of a narrative. Both mechanisms push in the same direction of an increased mobilization of those with larger misperceptions.

- H16: the narratives will increase mobilization of those who have the larger "misperceptions".

A last set of hypotheses deals with the specific petitions chosen by the respondents. On this, we will posit that the statement will persuade individuals to sign the corresponding petition, however we still believe that negative consequences will make the techno-pessimist petition more signed:

- H17: on aggregate, in each treatment respondents will sign more the petitions related to the corresponding statement.
- H18: the techno-pessimistic petition will get more signatures than the techno-optimistic one, with the balanced petition standing in between.

Furthermore, we will consider as an additional within-subject tests the role that previous beliefs and misperceptions as well as exposure to automation have in increasing or decreasing polarization when it comes to the choice of the petition to be signed. The hypotheses on this mirror H11 and H12. Of course, of both outcomes – mobilization and specific petition – we will also consider the influence of individual characteristics such as gender, age, education, living area, exposure to automation, occupation and political orientation.

Additional outcomes

Trust in several institutions: we expect techno-pessimistic narratives to reduce trust in all institutions, especially in tech tycoons. However, we believe preferences associated to trust to be stickier than policy preferences and willingness to support petitions, so we do not expect the changes to be statistically significant.

Chances of losing one's own job: previous surveys generally indicate that individuals believe they will not be affected by automation/AI as much as others. First, we expect to replicate this result. Second, we expect that out treatments will affect this assessment only marginally, because individuals will be more (over)confident about their job than about the overall impact at the economy level or about policy/political preferences.

Statistical analysis

As our hypotheses are either descriptive in nature or arise from treatments that are randomly assigned independently to different individuals, our statistical analysis will rely on conventional non-parametric tests complemented by regression analysis. We are also interested in testing possible differences in relationships or treatment across groups, in particular gender, age, education, income, residence location, use of technology, feelings towards technology, risk preferences, occupation and its task content, industry, exposure to automation. To test the influence of exposure to automation we will rely on the IV identification strategy by Anelli et al. (2021), which uses occupation and industry together with a large set of socio-demographic characteristics to predict exposure to job loss for different individuals. Occupation and industry will be derived from the text analysis of open questions on the last job, on the specific tasks undergone during the job, and on the industry sector of the employer.

Our between-treatment hypotheses will be first tested with non-parametric tests, then with regression analyses including indicator variables for treatment status. Regression analysis will test for the same hypotheses controlling for demographic characteristics (gender, age, immigration status), socio-economic status (income; education; skill-level; employment status; we may include occupation instead of income if many people decline to report income), area of residence (using three macro-areas).

Within-treatment hypotheses will also be tested with non-parametric tests and with regression analysis, following the framework by Haaland et al. (2023). To extract quantitative information from our open-ended question and define a pre-treatment variable on political preferences towards automation and AI, we will use text analysis techniques such as NLP, sentiment analysis, LDA or other clustering procedures, unsupervised and supervised machine learning for classification, further confronting the text with dictionaries such as the LIWC dictionary.