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Are our values becoming more fit for artificial intelligence society? A longitudinal study of occupational values and occupational susceptibility to technological substitution

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ABSTRACT

Advanced technologies are changing our working life in unpredictable ways. Consequently, a fear of technologically induced mass unemployment has re-emerged. The increased precarity associated with the technological substitution of work could lead to a regression towards materialist values that are more accepting of authoritarianism and xenophobia. Crucially, these values are less associated with the skills demanded in future work, which tends to be depicted as demanding higher levels of innovation, creative and social skills that are associated with post-materialist values. Current research has thus far overlooked the cultural aspects of large-scale technological substitution of work, which this study illuminates. We investigate how the relationship between occupational values and occupational automatability has developed between 2002 and 2018 in Europe. The results demonstrate that occupational values have been rather stable throughout the period. Occupational values are not becoming more or less fit for artificial intelligence society as would be expected if the context becomes increasingly precarious or innovation-driven. The paper demonstrates that a cultural adaptation to this type of society has not yet occurred.

1. Introduction

The context of work is expected to change significantly as intelligent technologies, such as AI combined with advanced sensors and robotics, become capable of substituting a broader range of manual and abstract tasks (e.g., Ref. [1]. Even though the topic has been studied through many perspectives (see Ref. [2], how such disruption could affect culture is largely unexplored. Values are at the core of culture and develop as responses to opportunities and threats in the environment [3–5], and changes in value priorities indicate a broader cultural change [5]. By exploring how values have developed in occupations at different levels of risk for technological substitution during the past two decades, this study sheds light on the cultural consequences of technological substitution of work.

A major share of current scholarship on technological substitution and transformation of work concerns the economic consequences of labor substitution or the changing skill requirements, which has been evidenced for example in the automotive industry [6]. The main proposition in the current literature is that the tasks remaining after digital technologies substitute work are creative or social or they require physical adaptability (such as maintenance work) that complement the capacities of the advanced technologies [1,7–9]. Interest is growing in the psychological and social consequences of the forecasted technologically induced changes in work. Such interest relates to well-being [10,11] and fears of job loss [12], among other concerns. Because the technological change mainly affects certain types of tasks, it also has consequences for workforce readiness [13] and impacts person–job fit [14,15]. Furthermore, digitizing work has been demonstrated to disrupt person–job fit [16] and consequently decrease employee job satisfaction and organizational commitment (cf [17].

Building on Inglehart's modernization thesis, technological substitution of work affects societies more profoundly than is currently being discussed in the debate on the future of work. Since the Second World War, western societies have become more liberal and democratic as

Abbreviations: ESS, European Social Survey; AIS, Artificial Intelligence Society.
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living standards and existential security have increased. A radical change in employment security and consequently declining living standards and existential security in artificial intelligence society (AIS) would counter the development in liberal western democracies [5]. A key factor in this process is the rising inequality or "superstar" economy, which operates on a winner-take-all principle; in this scenario, production requires a fraction of workers compared to traditional manufacturing industries [5]. When low-skilled workers are left with menial jobs (e.g., gig work; task-based work such as Amazon's mechanical Turk), their living standards decrease. Consequently, there is a fear that the liberal, or post-materialist, societies that have developed since the Second World War are regressing towards materialism, resulting in an increased acceptance of xenophobia and authoritarianism.

How technological substitution could affect national or regional culture is largely overlooked in the current discussions on technological substitution of work. Inglehart's [5] chapter on how the uncertainty characterizing AIS would affect cultures is one of the few attempts to consider the cultural consequences of technological substitution. Focusing on a global sample of countries, he illustrates that when the standard of living improves, societies tend to become less conformist and more self-expressive. Where living standards decrease and life becomes more precarious, as would occur in AIS, societies become more accepting of authoritarianism and xenophobia. Voting behavior in the US demonstrates the relationship between precarity and greater acceptance of authoritarian and xenophobic politicians. The higher the unemployment in a region, the higher the support for authoritarian leaders [18]. Indeed, in regions where work previously employing humans has been replaced by automation, individuals had a stronger tendency to vote for Donald Trump in the 2016 US presidential election [19].

This cultural change would become reality in AIS if advanced robotics and digital technologies change the *nature* and *availability* of work significantly. Driven by new developments in artificial intelligence, the internet of things, and robotics, intelligent technologies are expected to subsume a large portion (5%–47%) of the work characterized by structure or routine [9,20,21]. However, critical voices are raised against these assessments both in terms of accuracy [22] and methodology [23]. Yet even critics agree that the role of advanced technology has grown in the workplace (e.g. Ref. [23]), and that there is a genuine risk that those with low levels of training are restricted to menial jobs [24,25]. Furthermore, the increased presence of technology at work changes the characteristics of occupations and the skills required to thrive in this new environment, requiring the workforce to retrain to remain competitive [13].

A single study has investigated how value priorities in occupations (i.e., occupational values) relate to an occupation's susceptibility to technological substitution (i.e., occupational automatability). Långstedt [15] showed that significant differences in occupational values exist between automatable and non-automatable occupations. By adopting a longitudinal perspective, in contrast to Långstedt's [15] snapshot, this study captures the long-term development of values in occupations at different levels of risk for technological substitution. Furthermore, by investigating the relationship between values and automation, it demonstrates how the relationship between occupational values and automatability has shifted from 2002 to 2018. The principal finding is that occupational values have changed during the observed period, but these changes do not appear to be connected to the occupational risk of automation; rather, they signal a societal change in the wake of the 2008 financial crisis.

This paper is outlined as follows: First, current research on technological substitution of work is reviewed. Second, the relationship between occupational values and occupational automatability is theorized and hypotheses are presented. Finally, the hypotheses are tested on data from the European social survey and the results are presented and discussed.

2. The cultural dimension of technological substitution of work

2.1. Technology and the polarization of the work force

A central driver of the debate on technological job replacement is the work of economist David Autor. He has attributed a decrease in the share of routine tasks in the labor market [26] and a polarization of the US workforce, i.e., an increase in the service sector and in high-paying jobs at the expense of middle-income work [27], to the technological substitution of routine manual and cognitive work. Technological substitution of work is thus characterized as *biased* toward routine tasks in the United States and Europe [28–30]. Mainly affected by this development are less-educated men [31], while women have moved to more demanding jobs and their position in the labor market has improved [32]. Others have been skeptical of the reality of the polarization consensus and criticized its simplified operationalization of quality work as regarding only salary level. Oesch and Piccitto [33] demonstrate that job polarization has not occurred in earnings, level of education, prestige, or job satisfaction in many European countries. In Britain, polarization is related to earnings, and even there the share of highest-paid jobs has increased threefold compared to the lowest paying jobs. This does not mean that technology is not replacing work; it shows that advanced economies are "most successful in the automation and offshoring of low-paid, low-skilled, and low-status occupations … [and] the job opportunities for workers with low qualifications will continue to shrink" [33]. The structural development of the labor market in Europe varies considerably across countries, and in the majority of countries, low-paid jobs have decreased and the mid- or high-paying jobs increased between 1996 and 2007 [34].

It is clear then that the consequences of implementing advanced technologies vary across countries. The institutional environment plays an important role in the diffusion of advanced technologies at work. How advanced technologies impact regions and countries is also dependent on the industry structure and how much routine or structured work is performed in the country. For example, Frey and Osborne [35] assessed that 47% of the US workforce could be replaced by advanced technologies. In comparison, Pajarinen and Rouvinen [36], using the same methodology, assessed that roughly a third of the Finnish workforce could be replaced by advanced technologies. A study from the OECD [20] illustrates this variation quite clearly. Building on a job-level approach, rather than occupation-level, the report calculated how large a share of the workforce in the OECD countries could be automated. The figures differ significantly from those of Frey and Osborne [35]. According to the report, the share of the workforce at high risk of being automated in the United States is 9%; the corresponding figure in Finland is 7% and in Germany, 12%. According to the report, those most vulnerable to automation are people without a degree from higher education and those in low-paid jobs. Adding to the heterogeneity of evaluations, a report by the McKinsey Global Institute [21] found that only 5% of jobs could be completely substituted by advanced technologies; however, over 50% would be affected by the technologies. Dierdorff and Ellington [13] clustered occupations according to their required skills and found that occupations form eight skill clusters. From these clusters they projected that only two clusters – production workers and construction and extraction occupations – would see their share of the workforce decrease during the period 2016–2026. The occupational groups architecture and engineering, education, management, installation and maintenance, office and administrative, and healthcare and technical would increase during that period based on the skills reported by workers in the O*NET database and the in-demand skills of AIS.

In Fig. 1, occupational data from the European Labor Force Survey[1] is categorized according to Frey and Osborne's [35] framework. It

[1] Dataset: LFSA_EGISED 2002–2018 European union, accessed 25/01/2021 23:00.

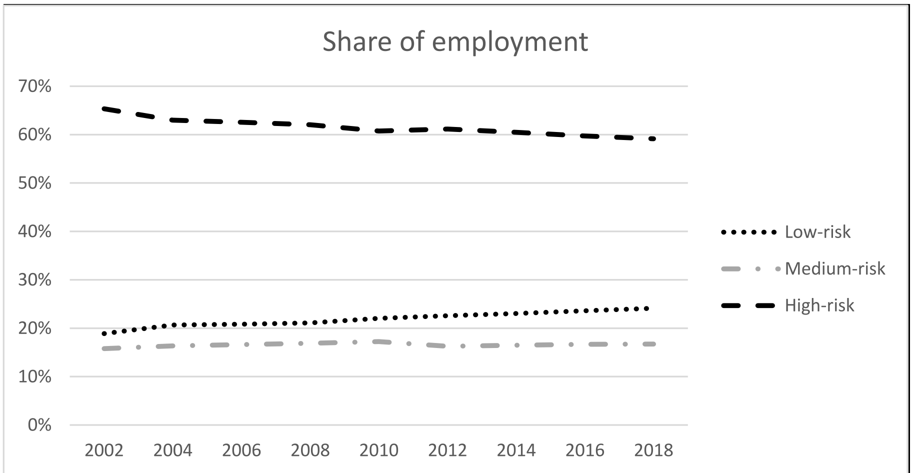

Fig. 1. The share of employment in occupations classified as high-, medium-, or low-risk by Frey and Osborne [9] in the European Union during the years 2002–2018.

implies that the share of employment in low-risk occupations have grown moderately (6% points [ppt]) during 2002–2018 and that this has occurred at the expense of high-risk occupations. The growth of the service sector partly balances out the impact of those occupations whose share of employment has decreased. It seems that the elementary workers' and technicians' (e.g., cleaners, gardeners) share of employment remains stable, while the shares of crafts, agriculture, machine operators and managers have decreased.

To summarize, the substitution of routine work creates a discrepancy between skills and the demands of work [38]. If work is automated to the extent that researchers have estimated, the skill supply and demand is likely to be unmet because repetitive and abstract tasks require different skill sets [7,38]. A challenge for workers is to transition from one occupational role to another, which requires new skills [13], and the lack of a sufficiently skilled workforce can slow the technological substitution of work [38]. The lack of sufficient skills to complement advanced technologies can have an adverse effect on the progress of automating work – making substitution incremental rather than disruptive. It is also in this context that values become relevant for the substitution of work [15]. Value priorities express what is worthwhile to pursue and how, thus affecting the skills that people acquire and the occupations they are attracted to (Refs. [39,40]), linking values to the technological substitution of work [15].

2.2. Basic human values

Values are a central aspect of culture and often used to quantify culture and compare cultures (e.g., Ref. [3]; [4]; [5]). Values in this context are cognitive representations of basic needs and have a motivational function; they express desired goals and the means to achieve them [41,37]. Values have evolved in response to three basic requisites of human existence: "needs of individuals as biological organisms, requisites of coordinated social interaction, and survival and welfare needs of groups" [37]; p. 4). Values, therefore, have a problem-solving and adaptive dimension (e.g., Refs. [5,42]. Schwartz [37] identified ten motivational values that represent basic needs (see Table 1 for definitions) and are organized in a two-dimensional motivational space (see Fig. 2): self-transcendence vs. self-enhancement and openness to change vs. conservation. The strength of Schwartz's [37] values model compared to other values models is that it demonstrates the relationship between values. The values next to each other are compatible, while those opposite each other are contradictory. For example, the conformity and self-direction values are logically incompatible and their negative association is empirically demonstrated globally (e.g., Ref. [37]. Those that value conformity strive to follow rules and norms

Table 1
The defining goals of Schwartz's [37] value types.

Upper-level value	Value type	Defining goal
Self-transcendence	Benevolence	Focus on the welfare of people with whom one is in close contact
	Universalism	Understanding, appreciation, tolerance, and protection for the welfare of *all* people and for nature
Openness to change	Self-direction	Independent thought and action – choosing, creating, exploring.
	Stimulation	Excitement, novelty, and challenge in life.
	Hedonism	Pleasure or sensuous gratification of oneself.
Conservation	Tradition	Respect, commitment, and acceptance of the customs and ideas that one's culture or religion imposes on the individual.
	Conformity	Restraint of actions, inclinations, and impulses likely to upset or harm others and violate social expectations and norms.
	Security	Safety, harmony, and stability of society, of relationships, and of self.
Self-enhancement	Power	Attainment of social status and prestige, and control or dominance over people and resources
	Achievement	Personal success through demonstrating competence according to social standards.

while those that cherish self-direction are more inclined to choose their own paths – even when they deviate from norms (see Table 1).

Values are shaped through the socialization process in which beliefs and norms are transferred to offspring through family, peers, and the broader social context [43]. Similarly, cultural groups' shared experiences shape the values adopted within them [44]. As with the exposure to automation, values are strongly affected by socioeconomic status (income) and levels of education. Individuals with lower income and education, whose positions tend to be more susceptible to automation, tend to prioritize conformist and traditional values over values of individualism and autonomy, while the opposite is true for affluent individuals [45]. Also, the availability of resources plays a crucial role in determining which values become prioritized. In contexts with a scarcity of resources, values pertaining to survival (security, tradition, conformity, power) are emphasized; individuals have limited options to pursue personal growth because ensuring the basic survival of oneself and one's offspring requires resources that guarantee that survival [5]. In contrast, in contexts where individuals do not need to worry about basic survival, resources to pursue personal growth are more readily available, as expressed in post-materialist values such as self-direction, hedonism, stimulation, and universalism [5]. If an individual places importance on a set of values that do not correspond to environmental affordances and restrictions, the values are not ideal for that context and inhibit adaptation [42]. Hence, as the requirements of the environment change, individuals with different value priorities could be expected to thrive. From this perspective, values are the result of adaptation to environmental threats and opportunities and adoption of goals that support success in an particular environment [5,42]. As technological substitution makes work more precarious and changes work requirements, different values are better adapted or "fit" for AIS than contemporary work.

2.3. Basic human values and automation

The way in which occupational automatability relates to human values is through the restrictions and opportunities in AIS once routine work is substituted. Given that people with different values thrive in different contexts and that routine-based jobs are considered most susceptible to technological substitution, values that are better adapted to creative or social work environments would become more important in automatable occupations over time. It could be expected that the share of people prioritizing well-adapted values over poorly adapted values would increase. Alternatively, the precarity associated with AIS increases the importance of values of conservation and self-transcendence as uncertainty increases and basic survival (income) is threatened by an unpredictable labor market. For example, Långstedt [15] demonstrates that conservation and self-enhancement values are more prominent in occupations susceptible to automation. These values are negatively associated with creativity and social skills in numerous studies (for a review see Ref. [46] or [15], indicating that those values are less beneficial in AIS. The routine intensive and structured tasks attract workers that prioritize conservation and self-transcendence values and consequently, work that fits the values prioritized in automatable occupations is substituted in AIS.

People holding similar values tend to be attracted to similar occupations (e.g. Refs. [39,47–49], which is the foundation for the relationship between occupational automatability and values. The positive effects of fit between values and work environment have long been established and demonstrated empirically. Work–values fit impacts job engagement, job satisfaction, and organizational identification positively [17,50], and it has a positive effect on well-being in general (see Ref. [51]; for a review). Therefore, fit is a desirable state for both organizations and workers, but it can be upset when the characteristics of jobs, such as tasks and workflows, are changed [52]. In AIS, the technological capabilities to substitute specific types of tasks change the work requirements and prerequisites for well-paid work, making values associated with demanded skills a better fit for the work environment in AIS.

Sagiv et al. [51] give examples of how the work context in tandem with values relates to adaptability and affects the well-being of workers. They consider the many opportunities that accountants are presented with to follow rules and regulations in accounting firms, while the accountancy context can "block creativity and imagination" (p. 75). Here, the environment provides advantages to thrive for those who value conformity, while it places those who pursue creativity at a disadvantage, with fewer opportunities to pursue their values, hence affecting well-being negatively [11]. Accordingly, the discrepancy between the values and the work context affects job satisfaction and change readiness negatively [17,53]. Both aspects can prolong the process of automation and inhibit the worker's adaptation to the post-automation work context.

What values are less and more beneficial in AIS? Previously, the values of self-transcendence and openness to change have been proposed as beneficial in relation to the skill requirements and the fit with the post-automated work environment [15]. Researchers connect these values positively to interests in non-automatable professions and the skills required within them, such as innovativeness, creativity and empathy [48,54–56]. In contrast, values related to conservation tend to correlate negatively with creativity and innovation (e.g. Refs. [54,55,57, 58], and self-enhancement values tend to correlate negatively with empathy and prosocial behavior (e.g., Refs. [56,59].

2.4. Formulation of hypotheses

Because people living in precarious contexts tend to express materialist values and life for people in automatable occupations becomes more precarious in AIS [5], we expect conservation and self-enhancement values to increase in importance in high-risk occupations. Thus, we propose the following hypotheses.

H1. The share of workers cherishing openness to change over conservation values declines in occupations at high and medium risk for automation and increases in low-risk occupations.

H2. The share of workers cherishing self-transcendence values over self-enhancement values decreases in occupations at high and medium risk and increases in low-risk occupations.

Following the idea that values are developed to solve the problems that are required for a functioning society [5,37,42], we could also expect that the correlation between values and automation weakens over time, as a result of an adaptation to AIS, i.e., high-risk occupations could adopt stronger openness-to-change and self-transcendence values. This would be illustrated as a weakening of the correlation between occupational values and occupational automatability as occupations become less distinguishable by their value priorities. Thus, we propose the following hypothesis that.

H3. The correlation between occupational values and occupational automatability decreases during the years 2002–2018.

Values are strongly related to level of education and income (e.g. Ref. [45], and automation is expected to strike hardest at those with low income and low levels of education (e.g., Ref. [20]. Thus, we expect that income and level of education in occupations explain much of the correlation between occupational values and automation. Thus, we propose the following two sub-hypotheses.

H3a. Income mediates the relationship between values and automation.

H3b. Level of education mediates the relationship between values and automation.

Value priorities are also intimately connected to gender [60]; [61]) and age ([4]; [5]. A gendered dimension of technological substitution has been demonstrated previously by Eriksson et al. [32] and Holzer [31]. Furthermore, occupations in Europe tend to be gender imbalanced (e.g., STEM vs. healthcare and education). Thus, we expect that age and gender mediate the relationship between occupational values and automation. Thus, we propose the following sub-hypotheses.

H3c. Gender mediates the relationship between values and automation.

H3d. Age mediates the relationship between values and automation.

3. Materials and methods

3.1. Data

To test the hypotheses, we used the European Social Survey (ESS) [62]. The survey is biannual, beginning in 2002 and currently ending in 2018. The ESS data classify respondents' occupations according to the ISCO-88 and ISCO-08 standards. The standards were merged and recoded using the manual for ISCO-08 and the accompanying correspondence table. Following that, the automatability of the occupations was attributed based on Frey and Osborne's [9] assessment of how susceptible occupations are to automation. Their assessment uses the American standard occupational classification (SOC) categorization. To translate the SOC classification to the ISCO classification, a correspondence table available at the US Bureau of Labor Statistics was used. When the correspondence table attributed several SOC categories with an automatability assessment to a single ISCO category, the mean automatability of the SOC categories was attributed to the ISCO category. Furthermore, each ISCO category with less than 100 respondents was merged with its parent category (e.g., 1112 was merged with 1100). This resulted in, on average, 82 occupations per round ranging between 77 (round 1) and 126 (round 8). ISCO categories with less than 100 respondents after the merger were omitted from the occupational-level analyses pertaining to hypothesis 3 and its sub-hypotheses. The SPSS syntax for constructing the dataset is available from the corresponding author. The *values, age, education level, gender,* and *household income decile* variables are derived from the ESS dataset by calculating the means of each occupation, which constitutes the dataset for performing the correlational analyses. Table 2 contains the means and standard deviations for each control variable across the samples. The share of female respondents in low-risk occupations is 56.1%, male 43.9%; in medium-risk occupations, female 56.5%, male 43.5%; and in high-risk occupations female 51.9%, male 48.1%.

3.2. Method

To measure values, Schwartz's PVQ-21, which is incorporated in the ESS, was used. In the PVQ-21, respondents reply to the question "How much like you is this person?" followed by a gender-matched statement: "He believes that people should do what they're told. He thinks people should follow rules at all times, even when no one is watching" (Conformity). The questionnaire consists of 21 items that the respondent replies to on a six-item scale ranging from "not like me at all" to "very much like me".

The measure has been tested extensively and found to produce the value structure on the individual and group levels and across age groups [63]. Despite previous criticism (cf. [64]), a more recent test of the psychometric features of the PVQ-21 deemed the questionnaire's measurement invariance appropriate [65]. The choice of the PVQ-21 over the longer and more precise measures of basic human values, such as the PVQ-57 or PVQ-40, is pragmatic. The ESS provides a unique opportunity to analyze occupations per year. For a review of measures for basic human values, see Roccas et al. [66]; and for a comparison of the statistical features between the PVQ-40 and PVQ-21, see Cieciuch and

Table 2
Mean of control variables across the across the total sample.

Risk level		Highest level of education	Household's net income decile	Gender	Age of respondent
Low-risk occupations	Mean	5.38	6.44	1.56	49.60
	N	57,896	53,853	66,739	66,548
	Std. Dev.	1.62	2.61	0.50	16.28
Medium-risk occupations	Mean	3.78	5.44	1.57	49.89
	N	65,734	61,411	77,498	77,302
	Std. Dev.	1.72	2.72	0.50	17.31
High-risk occupations	Mean	3.27	4.92	1.52	48.74
	N	98,401	89,330	116,823	116,484
	Std. Dev.	1.47	2.57	0.50	18.37
Total	Mean	3.97	5.48	1.55	49.30
	N	222,031	204,594	261,060	260,334
	Std. Dev.	1.81	2.70	0.50	17.55

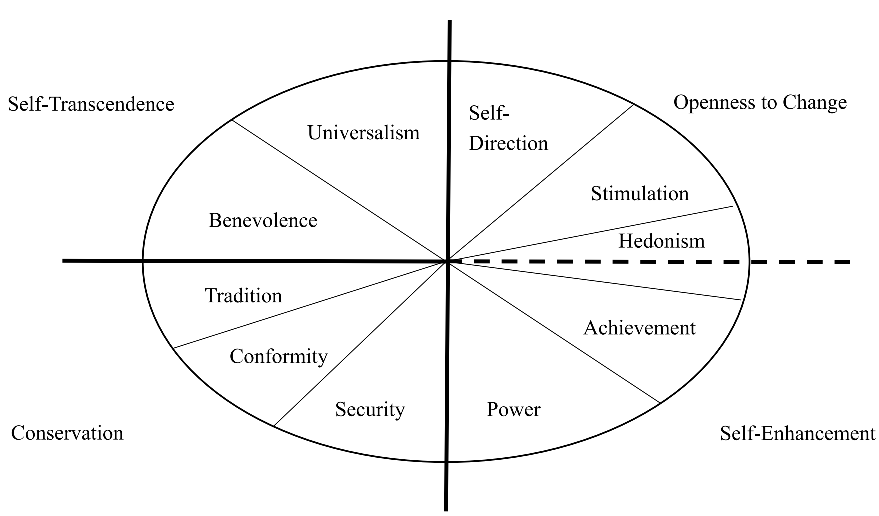

Fig. 2. Schwartz [37] value structure that represents the relationship between values.

Table 3
Examples of Frey and Osborne [9] Occupational automatability assessments.

Risk category	Automation probability	Occupation
High-risk occupations	0.96	Office clerks, general
	0.99	Title examiners, abstractors, and searchers
	0.99	Telemarketer
Medium-risk occupations	0.38	Interpreters and translators
	0.39	Home health aides
	0.41	Structural metal fabricators and fitters
Low-risk occupations	0.0028	Recreational therapists
	0.0035	Healthcare social workers
	0.0039	Dietitians and nutritionists

Davidov [67]. The Cronbach's alpha reliability score was tested. For the conservation values type it is 0.70, for self-transcendence 0.72, for openness to change 0.72, and for self-enhancement values 0.72, and thus above the conventional 0.7 threshold for acceptable reliability [68].

To measure the automatability of the occupations, Frey and Osborne's [9] index of occupational automatability was used (see examples in Table 3). The index was constructed based on the O*NET database of occupational task characteristics. They used nine O*NET variables to operationalize three engineering bottlenecks for substituting occupations with technology: 1) perception and manipulation (finger dexterity, manual dexterity, cramped workspaces and awkward positions), 2) creative intelligence (originality, fine arts), and 3) social intelligence (social perceptiveness, negotiation, persuasion, assisting and caring for others). Based on an expert panel's assessment of the automatability of 70 occupations, a machine learning algorithm assessed the automatability of 702 occupations on a scale between 0.0 and 1.0. Frey and Osborne's [9] automatability scores were attributed to the occupation categories in the ESS dataset .

The correlational data analysis is performed on the occupational level. Occupations tend to involve similar tasks and requirements from workers; they cut across industries, organizations and jobs to produce practical and data-driven insights [13]. Occupations are thus a relevant level of analysis concerning the future of work. The assessment by Frey and Osborne [9] used for classifying the occupations in this study is based on occupational-level data, and thus our analysis operates on the same level, avoiding cross-level issues and maintaining the analysis at the same level as the constructs (i.e., occupations; [69]. All analyses were performed in IBM's statistical software SPSS.

To test hypotheses 1 and 2, individual-level data were used. First, the occupations were classified into low-, medium-, and high-risk occupations following [9] framework (i.e., 0–0.3 = low-risk, 0.301–0.7 = medium-risk, and 0.701–1.0 = high-risk) (see Table 4 for means and standard deviations). Second, whether the individual prioritized openness to change over conservation was calculated by subtracting the score of conservation values from openness to change values. Following that, scores below 0 were dummy coded as "Values conservation over openness to change," 0 was coded as "Values openness to change equally," and scores above 0 were coded as "Values openness to change over conservation" in a new variable. The identical procedure was done for self-transcendence vs. self-enhancement. Following that, crosstabs were run with the new variables on the rows and the automation classification in columns, and the results were split by round. This produced the timeline in Figs. 3 and 4.

To test hypothesis 3 and its sub-hypotheses, we calculated Pearson correlations between automation and the four upper-level value types

Table 4
Means and standard deviations of values across the total sample.

Risk level		Conservation	Self-transcendence	Openness to change	Self-enhancement
Low-risk occupations	Mean	−0.02	0.69	−0.13	−0.52
	N	65,345	65,351	65,362	65,354
	Std. Dev.	0.63	0.54	0.60	0.57
Medium-risk occupations	Mean	0.13	0.65	−0.21	−0.55
	N	75,612	75,618	75,613	75,620
	Std. Dev.	0.63	0.53	0.63	0.59
High-risk occupations	Mean	0.18	0.57	−0.24	−0.51
	N	113,506	113,507	113,493	113,501
	Std. Dev.	0.62	0.53	0.64	0.59
Total	Mean	0.12	0.62	−0.20	−0.52
	N	254,463	254,476	254,468	254,475
	Std. Dev.	0.63	0.53	0.63	0.59

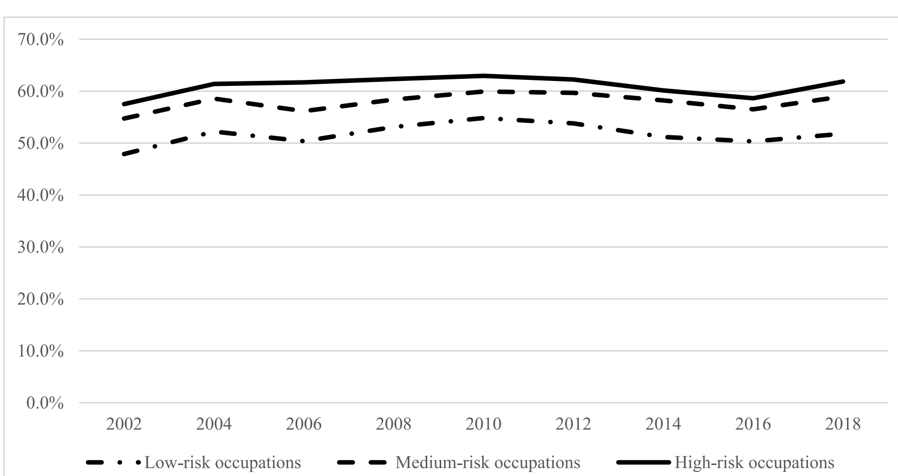

Fig. 3. Share of workers that value conservation over openness to change.

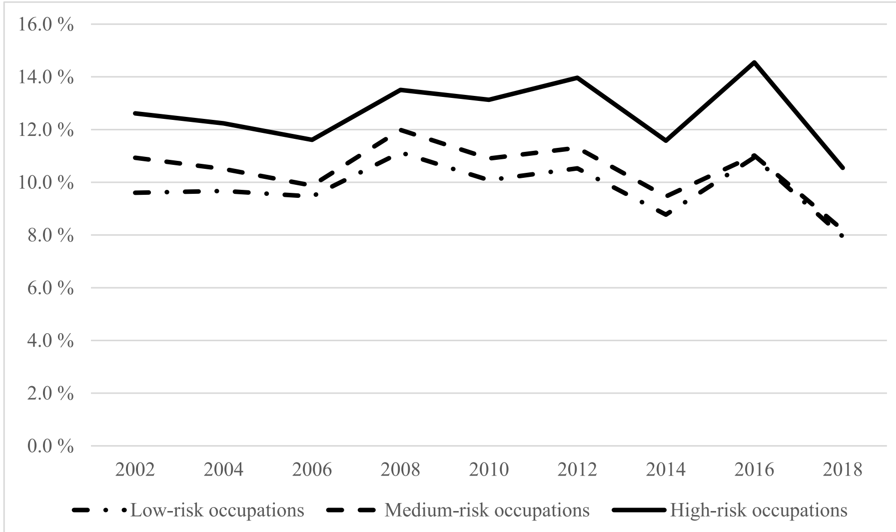

Fig. 4. Share of workers that value self-enhancement over self-transcendence.

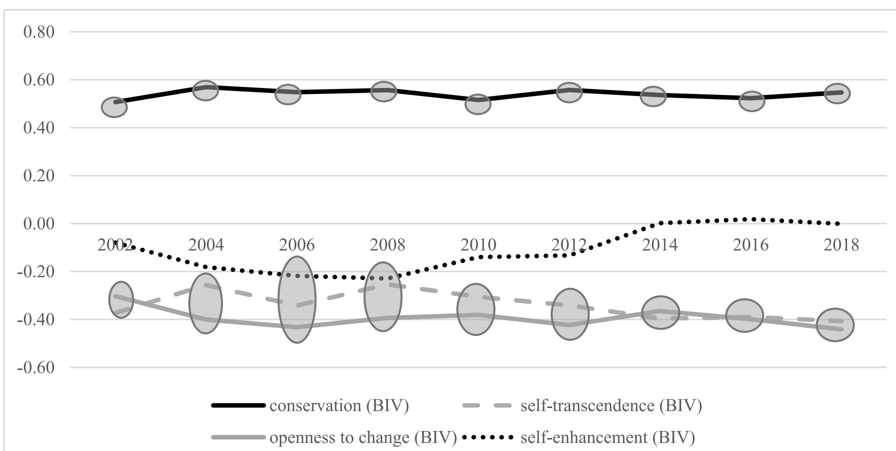

Fig. 5. Bivariate (BIV) correlations between occupational values (ISCO 4-digit) and susceptibility to automation.

controlling for the sub-variables *income, age, level of education,* and *gender* for each round. The analysis was performed at the occupational level and correlated the occupational mean scores with the occupational automatability scores derived from Frey and Osborne [9]. The results of these calculations are presented in Figs. 5–9 and in Appendix 1.

4. Results

4.1. Hypotheses 1 and 2 changes in the value priorities in high-, medium-, and low-risk occupations

To understand if changes in the values across the period have occurred, the share of workers valuing conservation over openness to change and self-enhancement over self-transcendence was calculated for each year. The above discussion indicate what values are rewarded in the contemporary context. It follows that the better-adapted values should be more pronounced in the low-risk occupations – that arguably represent occupations that comprise resources and rewards for contemporary and future working life. As could be expected based on the income and workforce discussion above and Långstedt's [15] seminal work, the share of workers valuing openness to change over conservation values is considerably higher in low-risk occupations than in high- and medium-risk occupations. This difference is relatively stable throughout 2002–2018 as the pattern is similar for the categories. Despite the conservation values being more pronounced in high-risk occupations throughout the period, there are yearly changes in the share of people valuing conservation over openness to change and the differences between the occupational groups varies yearly. For example, Fig. 3 demonstrates that the difference between medium-risk occupations and high-risk occupations more than doubles in 2006 compared to 2016 (5.5 ppt and 2.1 ppt, respectively).

The share of people valuing self-enhancement over self-transcendence is higher in the high-risk than in the low-risk occupations. Thus, in occupations that resemble work in the future, self-enhancement values are less pronounced than in jobs that are expected to be replaced by technology. While the pattern is very similar across the categories, the differences between the categories change. Whereas the self-enhancement values are constantly more pronounced in the high-risk category, the difference between medium- and low-risk occupations differ across the years. 2016 and 2006 seem to be exceptional years where the priorities of the categories converge (difference 0.1 ppt), while the differences are larger in previous years (e.g., 2002 = 1.3 ppt). The specific scores are reported in Appendices 1 and 2.

Hypotheses 1 and 2 are only partially supported by the data. Conservation values have become more pronounced in high-risk and medium-risk occupations, with the exception of 2016, but this applies to low-risk occupations as well. A similar, but more jagged, pattern is discernible regarding valuing self-enhancement over self-transcendence. The share valuing self-enhancement over self-transcendence does not indicate a clear pattern, despite an increase in 2008 and 2016. Thus, we partially reject hypotheses 1 and 2: The importance of conservation values has increased in medium- and high-risk occupations, but it has not decreased in low-risk occupations. While the share of workers valuing self-enhancement over self-transcendence has increased for a period (2008–2016) in the high- and medium-risk occupations, low-risk occupations follow a similar pattern.

4.2. *Hypothesis 3 the relationship between occupational values and automatability*

Next, the results of the Pearson and partial correlations between occupational automation and occupational values are presented. The results are presented according to values rather than sub-hypotheses to make the control variables' effect clearer. Each significant correlation is colored gray, and tables with the specific correlations and number of cases are found in Appendix 1.

Examining hypothesis 3, that the relationship between occupational automatability and the value types decreases over the period. The hypothesis is partly supported by the analysis. Self-enhancement values become less correlated with automatability during the period. The trajectory that self-transcendence values illustrate shows that the negative correlation grows over the measured period. The values of openness to change and conservation, however, maintain a similar correlation with automation throughout the period. Thus, hypothesis 3 is partially rejected; even though correlations between self-enhancement and occupational automatability decreased and became insignificant, correlations between conservation, openness-to-change values and automatability did not change during the period.

Hypotheses 3a, b, c, and d regarding openness-to-change values are partially supported. Fig. 6 demonstrates that education and income partially mediate the correlation between openness to change and occupational automatability, and age moderates it, thus providing support for the hypotheses. Gender does not affect the relationship significantly. The temporal dimension of the relationship between conservation and occupational automatability is visible as the effect of income and education changes over the timespan, becoming weaker and stronger, respectively.

Hypotheses 3a, b, c, and d regarding conservation are partially supported. The data demonstrate that education mediates the correlation between automatability and conservation values from 2010 onwards while its effect is considerably weaker in the prior years (Fig. 7) In contrast, the income variable mediates the correlation 2002–2010, but its mediating effect decreases 2012–2018. Age moderates the relationship and gender does not have a considerable effect on the relationship.

Hypotheses 3a, b, c, and d regarding self-transcendence are partially supported (Fig. 8). As with the previous correlations, the effect of the control variables varies during the period. Especially the effect of income decreases in 2008–2012 compared to the period before and after – although remaining weaker in 2018 than in 2002. Age does not have a noteworthy effect on the relationship between self-transcendence and automation. In contrast to the values of conservation and openness to change, the analysis demonstrates that gender affects the relationship between self-transcendence values and occupational automatability.

Hypothesis 3a, b, c, and d regarding self-enhancement are partially supported (Fig. 9). Income and level of education moderate the relationship between self-enhancement values and occupational

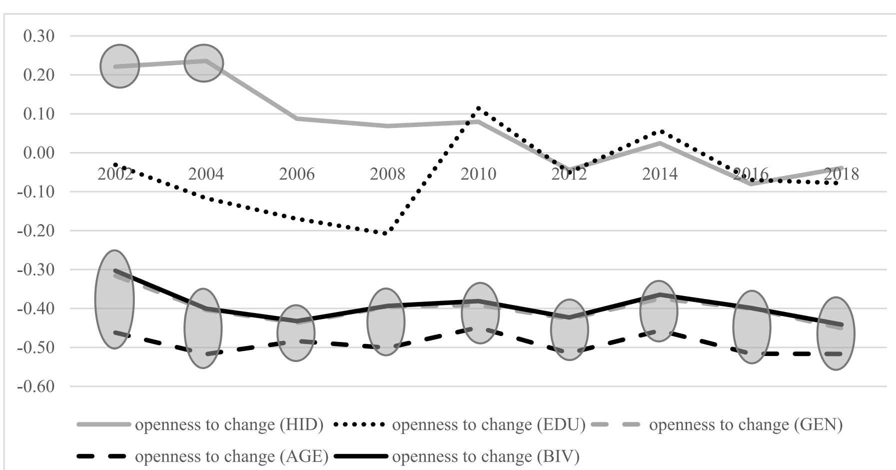

Fig. 6. Bivariate (BIV) and partial correlations between occupational automatability and Openness-to-change values (controlling for occupational mean Highest income Decile (HID); Level of Education (EDU); Gender (GEN); Age (AGE)).

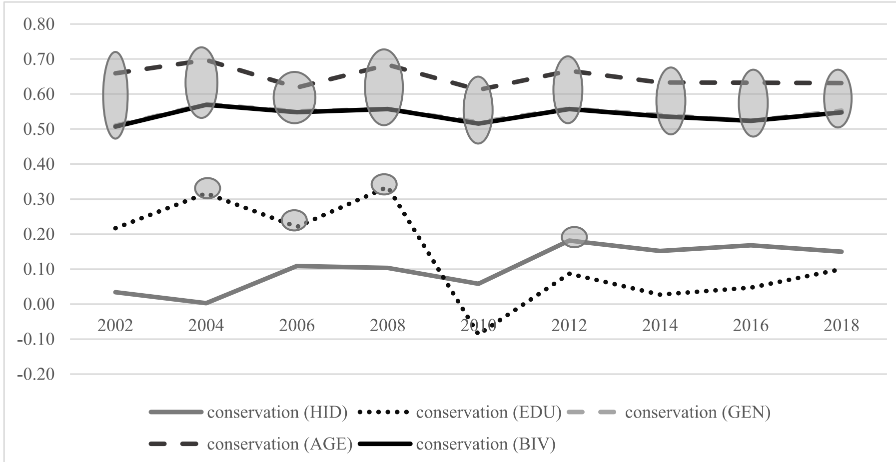

Fig. 7. Bivariate (BIV) and partial correlations between occupational automatability and Conservation values (controlling for occupational mean Highest income Decile (HID); Level of Education (EDU); Gender (GEN); Age (AGE)).

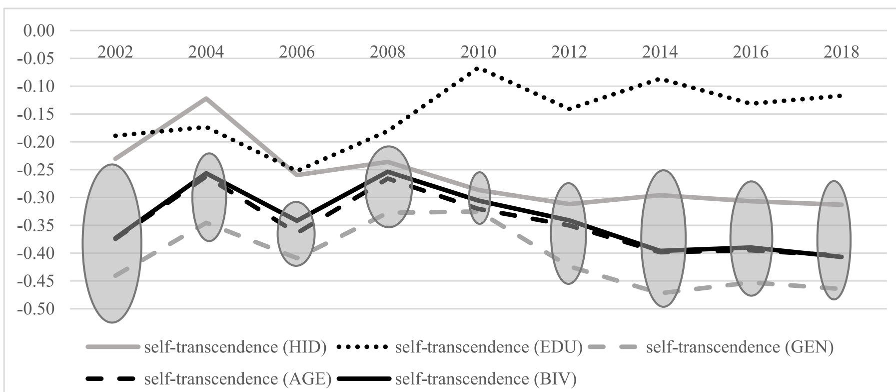

Fig. 8. Bivariate (BIV) and partial correlations between occupational automatability and Self-transcendence values (controlling for occupational mean Highest income Decile (HID); Level of Education (EDU); Gender (GEN); Age (AGE)).

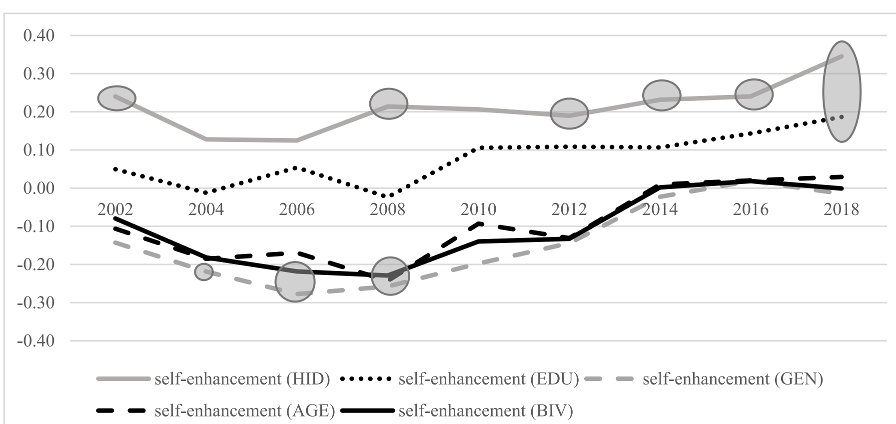

Fig. 9. Bivariate (BIV) and partial correlations between occupational automatability and Self-Enhancement values (controlling for occupational mean Highest income Decile (HID); Level of Education (EDU); Gender (GEN); Age (AGE)).

automatability. When controlling for the variables, the relationship becomes positive, but the effect grows weaker from 2014 onwards, demonstrating the importance of considering the temporal dimension of the relationship. Gender and age have minor effects on the correlation 2006–2010 that weakens 2012 forward.

5. Discussion

We set out to explore if values are becoming more "fit" for artificial intelligence society. We observed how the share of people valuing conservation over openness to change and self-enhancement over self-transcendence changes from 2002 to 2018. We also observed how the relationship between values and automation varied during the same period. The longitudinal data provided an opportunity to observe whether a cultural change has occurred in occupations at different degrees of risk for technological substitution (i.e., their "automatability"). A central driver of the potential cultural change is that the skill requirements of work have changed [26,29] and are expected to change further in the future [38], becoming more social and creative [1], while making working life significantly more precarious for some [5]. Långstedt [15] argued that this technologically driven change may create a discrepancy between work and values, potentially leading to decreased job satisfaction and engagement, while affecting the well-being of workers negatively [11]. People tend to find jobs that to some extent correspond to their values. If they are unable to do so, it could involve a loss of the meaningfulness of work and, more concretely, cause difficulty in finding employment.

The results demonstrate that little change has occurred in occupational value priorities during the 16-year period. Occupational values are not becoming more fit for the future of work (i.e., the values of self-transcendence and openness to change are not becoming more prevalent). Importantly, the data do not support the contention that occupations are becoming more materialist, and by extension less innovative, as could be expected based on Inglehart's [5] discussion. Instead, value priorities in the occupational groups are rather stable, demonstrating only small variations in priorities. The potential cultural consequences of AIS are thus absent in the data.

This absence can be explained by multiple reasons. The data are constructed based on an international sample, considering that precarity and opportunities may vary considerably nationally and regionally as Berger and Frey [70] indicate. Workers in Nordic welfare states have a different level of security than those in countries with more restricted social support policies, such as Germany or the UK. As such, local signs of the precarity or an adaptation to a more innovation-driven work environment may not be evident in data aggregated to a European level of analysis. Furthermore, the cultural consequences of technological substitution may not yet be detectable because the technologies are yet to be commodified and several engineering bottlenecks persist for large-scale technological substitution of work. Furthermore, the data analysis excluded the unemployed and self-employed, who are in a very different situation than the employed in terms of benefits and livelihood.

A central feature of artificial intelligence society is that the environment becomes more precarious as a result of technological substitution of work and the inequalities that follows [5]. This development leads to a more materialist society. Indeed, the share of workers valuing conservation over openness to change and self-enhancement over self-transcendence increases in importance during the analyzed period. However, the development is weak and U-shaped rather than linearly increasing, as would be expected if European societies were becoming more materialist. In addition, the development should mainly affect the high-risk and medium-risk occupations as these are the ones whose lives are becoming more precarious. In contrast, the data show that also low-risk occupations follow a gentle U-shape regarding both value types (Figs. 3 and 4). Because all three occupational categories follow a similar pattern, the data demonstrate a societal, rather than occupational, change in value priorities.

Even though all three occupational categories follow the U-shape, it is noteworthy that the differences between the categories are largely maintained throughout the period. Although this excludes the idea that values are becoming more polarized between high- and low-risk occupations, it illustrates that occupational value differences have been reproduced throughout the last two decades, indicating little adaptation to the forecasted changes in work requirements. In light of the results (Figs. 3 and 4), the precarity following AIS will not only affect those in automatable occupations but also workers in non-automatable professions. This supports Inglehart's [5] argument that artificial intelligence society is characterized by values that indicate less innovation and higher acceptance of authoritarian figures.

The results of the correlational analysis of occupational values and occupational automatability shows that the relationship is not stable, especially when controlling for income and education level. The results demonstrate that the negative relationship between self-transcendence values and automatability has become stronger from 2008 forward. The relationship between occupational automatability and self-enhancement values has simultaneously grown weaker, while the conservation and openness to change values maintain a rather stable relationship to occupational automatability. While the reason for this change can only be speculated upon, it seems likely that it relates somehow to the financial crises in 2008. Perhaps companies substituted routine jobs with technological solutions as suggested by Hershbein and Kahn [71]; which then made the choice of new jobs salient, and those that value self-transcendence become more attracted to and attractive for employment in non-automatable occupations.

That income and education mediate much of the relationship between occupational values and automatability is not surprising since both values and automatability are intimately related to both variables. Relating to AIS, it brings forth the social inequalities that affect which values are prioritized and consequently which skills are acquired. Conservation values are indeed more pronounced in automatable occupations throughout the period. Considering that the attained level of education mediates most of the correlation between occupational values and automatability, the need to provide those with low-income access to education is crucial for their future. However, occupational interests and values are largely shaped by the individual's environment (e.g. Ref. [45]), and thus the issue is related to the larger questions of income disparities and class.

Both age and gender had little impact on the relationship between occupational values and automatability. Even though gender has been connected to the technological substitution of work in the Nordic countries [32], the results indicate that gender differences explained very little of the relationship between occupational values and automatability in our data. While gender weakens correlations between self-transcendence and automatability, it only affects the correlations between the other value types sporadically. Controlling for average age strengthened the correlations between openness to change and conservation and occupational automatability throughout the period. It weakened the relationship between self-enhancement values and had little effect on self-transcendence values. The result is somewhat surprising, considering that age is closely related to values [72].

The longitudinal perspective turned out to be a valuable approach because it provides a more wholesome picture than the snapshot provided by Långstedt [15]. It showed that neither occupational values, their relationship to occupational automatability, or the control variables behaved similarly throughout the period. Consider how different the results would be about self-enhancement's relationship to automation in 2004 and 2016 (on which Långstedt based his 2021 study). In 2004, the value type correlates negatively with occupational automatability while in 2016, the correlation is insignificant; furthermore, the effect of income on the relationship would have been considerably more pronounced in 2016 than in 2004. Thus, this study illustrates the fundamental importance of longitudinal studies in social sciences.

5.1. Conclusions

In conclusion, there are changes in value priorities and the relationships between occupational values and occupational automatability throughout the studied period. There is, however, no indication of an increasing value divergence or convergence between occupations at high, medium, or low risk for technological substitution, and changes in value priorities are unimpressive. The value priorities in occupations are clearly reproduced throughout the period and show little adaptation to increased demands for innovation or increased precarity associated with AIS. Since technological capabilities can develop rapidly, we cannot conclude that occupational values will not polarize in the future based on the past. However, we can conclude that as the context becomes more precarious, it not only affects the value priorities of high- and medium-risk occupations. To ensure future fit, policymakers need to consider the socialization of individuals in different contexts and to establish policies that increase the existential security of individuals; then their values are more likely to become fit for work in AIS than through increased competition.

5.2. Limitations and future trajectories

This is a first study on the development of occupational values in occupations at different levels of susceptibility for technological substitution. This necessarily involves a level-of-analysis problem. Though the occupational level has been advocated as a relevant level of analysis for detecting larger changes in the work context (e.g. Ref. [13]), it poses some limitations. First, occupations are rather diverse in terms of job descriptions and specialization, which means that jobs vary in the tasks that they include depending on how companies have organized work and defined roles and responsibilities. An aggregate level, such as the occupational level, cannot capture the individual differences in jobs (e.g., Ref. [20]. This requires a measure through which individual workers could describe the tasks they perform.

Another important trajectory for future research would be to compare different automatability indices to improve our understanding of occupational automatability and assess their accuracy. Even if they tend to rest on the same assumption that low-income and low-skill workers are at highest risk for substitution, replicating this study by using a different automation index could provide valuable information on the relationship between values and work automatability.

Furthermore, research on what makes work automatable is scarce, and close consideration of which jobs companies seek to automate should be considered when assessing their automatability. As recent research has demonstrated, even though work *can* be automated it *should not* necessarily be substituted with technology [73]. Technology is not a guarantee for improved products and services. Furthermore, a central question is whether decision-makers in companies *want* to replace workers with technologies. The existence of a technology does not determine its use or utility.

Another issue pertaining to the level of analysis is that the relationship between values and other variables can behave differently at an aggregate level. For example, on the national level, self-enhancement tends to be associated with lower GDP. Yet, on the individual level it is often associated with personal wealth. Therefore, the relationship between technological substitution and values may vary depending on the level at which the study is performed. Thus, individual-level studies of the relationship between values and job automatability are needed.

Developing a method that considers what kind of work decision-makers aim to replace and measures the task constitution of jobs at an *individual* level would enable studying multiple psychological and social constructs in relation to the automatability of work. Such a measure would increase our understanding of the organizational, psychological, and social impacts of artificial intelligence society.

Finally, the data do not comprise the unemployed and hence do not comprise those that might already have been replaced by technology. This is one future trajectory that needs to be further explored. For example, are unemployed that express values fit for AIS more likely to find employment than those that prioritize conservation and self-enhancement?

Author statement

Långstedt J.: conceptualization, methodology, data-analysis, writing original draft, review and editing, visualization, analysis, data processing and analysis. Spohr, J.: Data-analysis, review and editing. Hellström M.: review and editing, conceptualization.

Data availability

European Social Survey rounds 1-9 (available at: www.europeansocialsurvey.org)

Appendix 1. Yearly correlations

Control Variables	Variables	2002			2004			2006			2008		
		Correlation	Significance (2-tailed)	df	Correlation	Significance (2-tailed)	df	Correlation	Significance (2-tailed)	df	Correlation	Significance (2-tailed)	df
Mean household income decile	OA	1		0	1		0	1		0	1		0
	CON	0.03	0.77	74	0.00	0.98	77	0.11	0.33	79	0.10	0.35	82
	S-TRA	−0.23	**0.05**	74	−0.12	0.28	77	−0.26	**0.02**	79	−0.24	**0.03**	82
	OTCH	0.22	**0.05**	74	0.24	**0.04**	77	0.09	0.44	79	0.07	0.54	82
	S-ENH	0.24	**0.04**	74	0.13	0.26	77	0.12	0.27	79	0.21	**0.05**	82
Mean highest level of education	OA	1.00		0	1.00		0	1.00		0	1.00		0
	CON	0.22	0.06	74	0.32	**0.00**	77	0.22	**0.05**	79	0.33	**0.00**	82
	S-TRA	−0.19	0.10	74	−0.17	0.13	77	−0.25	**0.02**	79	−0.18	0.10	82
	OTCH	−0.03	0.79	74	−0.12	0.30	77	−0.17	0.13	79	−0.21	0.06	82
	S-ENH	0.05	0.67	74	−0.01	0.91	77	0.05	0.63	79	−0.02	0.83	82
Mean gender	OA	1.00		0	1.00		0	1.00		0	1.00		0
	CON	0.51	**0.00**	74	0.57	**0.00**	77	0.55	**0.00**	79	0.56	**0.00**	82
	S-TRA	−0.44	**0.00**	74	−0.35	**0.00**	77	−0.41	**0.00**	79	−0.33	**0.00**	82
	OTCH	−0.32	**0.01**	74	−0.40	**0.00**	77	−0.44	**0.00**	79	−0.40	**0.00**	82
	S-ENH	−0.14	0.22	74	−0.22	**0.05**	77	−0.28	**0.01**	79	−0.26	**0.02**	82
Mean age	OA	1.00		0	1.00		0	1.00		0	1.00		0
	CON	0.66	**0.00**	74	0.70	**0.00**	77	0.62	**0.00**	79	0.68	**0.00**	82
	S-TRA	−0.37	**0.00**	74	−0.26	**0.02**	77	−0.36	**0.00**	79	−0.27	**0.01**	82
	OTCH	−0.46	**0.00**	74	−0.52	**0.00**	77	−0.48	**0.00**	79	−0.50	**0.00**	82
	S-ENH	−0.11	0.36	74	−0.19	0.10	77	−0.17	0.13	79	−0.24	**0.03**	82
Bivariate	OA	1		0	1		0	1		0	1		0
	CON	0.51	**0.00**	77	0.57	**0.00**	80	0.55	**0.00**	82	0.56	**0.00**	85
	S-TRA	−0.37	**0.00**	77	−0.26	**0.02**	80	−0.34	**0.00**	82	−0.25	**0.02**	85
	OTCH	−0.30	**0.01**	77	−0.40	**0.00**	80	−0.43	**0.00**	82	−0.39	**0.00**	85
	S-ENH	−0.08	0.49	77	−0.18	0.11	80	−0.22	**0.05**	82	−0.23	**0.03**	85

Control Variables	Variables	2010			2012			2014			2016			2018		
		Correlation	Significance (2-tailed)	df	Correlation	Significance (2-tailed)	df	Correlation	Significance (2-tailed)	df	Correlation	Significance (2-tailed)	df	Correlation	Significance (2-tailed)	df
Mean household income decile	OA	1		0	1		0	1		0				1		0
	CON	0.06	0.60	83	0.18	**0.05**	116	0.15	0.11	108	0.17	0.06	126	0.15	0.10	118
	S-TRA	−0.29	**0.01**	83	−0.31	**0.00**	116	−0.30	0.00	108	−0.31	**0.00**	126	−0.31	**0.00**	118
	OTCH	0.08	0.47	83	−0.04	0.64	116	0.02	0.80	108	−0.08	0.37	126	−0.04	0.67	118
	S-ENH	0.21	0.06	83	0.19	0.04	116	0.23	0.01	108	0.24	**0.01**	126	0.35	**0.00**	118
Mean highest level of education	OA	1.00		0	1.00		0	1.00		0	1.00		0	1.00		0
	CON	−0.09	0.43	83	0.09	0.35	116	0.03	0.78	108	0.05	0.60	126	0.10	0.28	118
	S-TRA	−0.07	0.54	83	−0.14	0.13	116	−0.09	0.37	108	−0.13	0.14	126	−0.12	0.20	118
	OTCH	0.11	0.30	83	−0.05	0.59	116	0.06	0.56	108	−0.07	0.43	126	−0.08	0.40	118
	S-ENH	0.11	0.33	83	0.11	0.24	116	0.11	0.27	108	0.14	0.11	126	0.19	**0.04**	118
Mean gender	OA	1.00		0	1.00		0	1.00		0	1.00		0	1.00		0
	CON	0.52	**0.00**	83	0.56	**0.00**	116	0.54	0.00	108	0.52	**0.00**	126	0.55	**0.00**	118
	S-TRA	−0.33	**0.00**	83	−0.42	**0.00**	116	−0.47	0.00	108	−0.45	**0.00**	126	−0.46	**0.00**	118
	OTCH	−0.39	**0.00**	83	−0.43	**0.00**	116	−0.37	0.00	108	−0.40	**0.00**	126	−0.45	**0.00**	118
	S-ENH	−0.20	0.07	83	−0.14	0.12	116	−0.02	0.81	108	0.02	0.83	126	−0.01	0.88	118
Mean age	OA	1		0	1.00		0	1.00		0	1.00		0	1.00		0
	CON	0.61	**0.00**	83	0.67	**0.00**	116	0.63	0.00	108	0.63	**0.00**	126	0.63	**0.00**	118
	S-TRA	−0.32	**0.00**	83	−0.35	**0.00**	116	−0.40	0.00	108	−0.39	**0.00**	126	−0.40	**0.00**	118
	OTCH	−0.45	**0.00**	83	−0.51	**0.00**	116	−0.46	0.00	108	−0.52	**0.00**	126	−0.52	**0.00**	118
	S-ENH	−0.09	0.40	83	−0.13	0.16	116	0.01	0.92	108	0.02	0.82	126	0.03	0.75	118
Bivariate	OA	1		0	1		0	1		0	1			1		0
	CON	0.52	**0.00**	86	0.56	**0.00**	119	0.54	0.00	111	0.52	**0.00**	129	0.55	**0.00**	121
	S-TRA	−0.31	**0.00**	86	−0.34	**0.00**	119	−0.40	0.00	111	−0.39	**0.00**	129	−0.41	**0.00**	121
	OTCH	−0.38	**0.00**	86	−0.42	**0.00**	119	−0.36	0.00	111	−0.40	**0.00**	129	−0.44	**0.00**	121
	S-ENH	−0.14	0.20	86	−0.13	0.15	119	0.00	0.98	111	0.02	0.84	129	0.00	0.99	121

OA = Occupational Automatability, CON = Conservation, S-Tra = Self-Transcendence, OTCH = Openness to change, S-Enh = Self-enhancement. Statistically significant correlations are bolded ($p < .05$).

OA = Occupational Automatability, CON = Conservation, S-Tra = Self-Transcendence, OTCH = Openness to change, S-Enh = Self-enhancement. Significant correlations are bolded ($p < .05$).

Appendix 2. Shares of workers valuing self-enhancement (self-enh) over self-transcendence (self-trans)

Round	Risk level	Values self-enh more than self-trans		Values self-trans more than self-enh		Values self-trans and self-enh equally		Total	
		Count	% within Risk level	Count	% within Risk level	Count	% within Risk level	Count	% within Risk level
1	Low-risk occupations	490	9.6%	4552	89.2%	61	1.2%	5103	100%
	Medium-risk occupations	729	10.9%	5858	87.9%	81	1.2%	6668	100%
	High-risk occupations	1254	12.6%	8522	85.7%	166	1.7%	9942	100%
	Total	2473	11.4%	18,932	87.2%	308	1.4%	21,713	100%
2	Low-risk occupations	528	9.7%	4887	89.5%	44	0.8%	5459	100%
	Medium-risk occupations	854	10.5%	7180	88.3%	95	1.2%	8129	100%
	High-risk occupations	1400	12.2%	9875	86.3%	166	1.5%	11,441	100%
	Total	2782	11.1%	21,942	87.7%	305	1.2%	25,029	100%
3	Low-risk occupations	538	9.5%	5095	89.6%	52	0.9%	5685	100%
	Medium-risk occupations	709	9.9%	6387	89.0%	84	1.2%	7180	100%
	High-risk occupations	1368	11.6%	10,256	87.1%	157	1.3%	11,781	100%
	Total	2615	10.6%	21,738	88.2%	293	1.2%	24,646	100%
4	Low-risk occupations	752	11.1%	5884	87.1%	119	1.8%	6755	100%
	Medium-risk occupations	1033	12.0%	7417	86.1%	168	1.9%	8618	100%
	High-risk occupations	1888	13.5%	11,805	84.4%	286	2.0%	13,979	100%
	Total	3673	12.5%	25,106	85.5%	573	2.0%	29,352	100%
5	Low-risk occupations	680	10.1%	5971	88.5%	95	1.4%	6746	100%
	Medium-risk occupations	887	10.9%	7121	87.5%	126	1.5%	8134	100%
	High-risk occupations	1872	13.1%	12,160	85.3%	227	1.6%	14,259	100%
	Total	3439	11.8%	25,252	86.7%	448	1.5%	29,139	100%
6	Low-risk occupations	1045	10.5%	8749	88.1%	132	1.3%	9926	100%
	Medium-risk occupations	1262	11.3%	9760	87.5%	136	1.2%	11,158	100%
	High-risk occupations	2228	14.0%	13,482	84.5%	241	1.5%	15,951	100%
	Total	4535	12.2%	31,991	86.4%	509	1.4%	37,035	100%
7	Low-risk occupations	788	8.8%	8104	90.2%	90	1.0%	8982	100%
	Medium-risk occupations	899	9.5%	8484	89.3%	118	1.2%	9501	100%
	High-risk occupations	1490	11.6%	11,216	87.2%	161	1.3%	12,867	100%
	Total	3177	10.1%	27,804	88.7%	369	1.2%	31,350	100%
8	Low-risk occupations	1048	10.9%	8382	87.5%	146	1.5%	9576	100%
	Medium-risk occupations	1144	11.0%	9103	87.7%	135	1.3%	10,382	100%
	High-risk occupations	2096	14.5%	12,063	83.7%	249	1.7%	14,408	100%
	Total	4288	12.5%	29,548	86.0%	530	1.5%	34,366	100%
9	Low-risk occupations	773	7.9%	8874	91.2%	84	0.9%	9731	100%
	Medium-risk occupations	834	8.2%	9221	90.6%	124	1.2%	10,179	100%
	High-risk occupations	1506	10.5%	12,539	87.8%	232	1.6%	14,277	100%
	Total	3113	9.1%	30,634	89.6%	440	1.3%	34,187	100%

Appendix 3. Cross tabulation of the share of workers valuing openness to change (O-2-C) over conservation (CON)

Round	Risk level	Values CON over O-2-C		Values O-2-C over CON		Values O-2-C and CON equally		Total	
		Count	% within Risk level	Count	% within Risk level	Count	% within Risk level	Count	% within Risk level
1	Low-risk occupations	2444	47.9%	2350	46.1%	309	6.1%	5103	100%
	Medium-risk occupations	3650	54.7%	2600	39.0%	419	6.3%	6669	100%
	High-risk occupations	5720	57.5%	3554	35.7%	671	6.7%	9945	100%
	Total	11,814	54.4%	8504	39.2%	1399	6.4%	21,717	100%
2	Low-risk occupations	2852	52.2%	2288	41.9%	320	5.9%	5460	100%
	Medium-risk occupations	4763	58.6%	2858	35.1%	510	6.3%	8131	100%
	High-risk occupations	7028	61.4%	3689	32.2%	729	6.4%	11,446	100%
	Total	14,643	58.5%	8835	35.3%	1559	6.2%	25,037	100%
3	Low-risk occupations	2862	50.4%	2438	42.9%	381	6.7%	5681	100%
	Medium-risk occupations	4033	56.2%	2682	37.3%	466	6.5%	7181	100%
	High-risk occupations	7265	61.7%	3787	32.2%	724	6.1%	11,776	100%
	Total	14,160	57.5%	8907	36.2%	1571	6.4%	24,638	100%
4	Low-risk occupations	3587	53.1%	2702	40.0%	466	6.9%	6755	100%
	Medium-risk occupations	5031	58.4%	2973	34.5%	612	7.1%	8616	100%
	High-risk occupations	8713	62.4%	4350	31.1%	910	6.5%	13,973	100%
	Total	17,331	59.1%	10,025	34.2%	1988	6.8%	29,344	100%
5	Low-risk occupations	3700	54.8%	2596	38.5%	452	6.7%	6748	100%
	Medium-risk occupations	4874	59.9%	2706	33.3%	552	6.8%	8132	100%
	High-risk occupations	8977	63.0%	4333	30.4%	949	6.7%	14,259	100%
	Total	17,551	60.2%	9635	33.1%	1953	6.7%	29,139	100%
6	Low-risk occupations	5339	53.8%	3915	39.4%	671	6.8%	9925	100%
	Medium-risk occupations	6656	59.7%	3714	33.3%	782	7.0%	11,152	100%
	High-risk occupations	9929	62.2%	4961	31.1%	1061	6.7%	15,951	100%
	Total	21,924	59.2%	12,590	34.0%	2514	6.8%	37,028	100%
7	Low-risk occupations	4598	51.2%	3801	42.3%	584	6.5%	8983	100%

(*continued on next page*)

(*continued*)

Round	Risk level	Values CON over O-2-C		Values O-2-C over CON		Values O-2-C and CON equally		Total	
		Count	% within Risk level	Count	% within Risk level	Count	% within Risk level	Count	% within Risk level
	Medium-risk occupations	5529	58.2%	3359	35.4%	609	6.4%	9497	100%
	High-risk occupations	7740	60.2%	4232	32.9%	894	6.9%	12,866	100%
	Total	17,867	57.0%	11,392	36.3%	2087	6.7%	31,346	100%
8	Low-risk occupations	4818	50.3%	4082	42.6%	675	7.0%	9575	100%
	Medium-risk occupations	5868	56.5%	3816	36.8%	699	6.7%	10,383	100%
	High-risk occupations	8449	58.6%	4875	33.8%	1082	7.5%	14,406	100%
	Total	19,135	55.7%	12,773	37.2%	2456	7.1%	34,364	100%
9	Low-risk occupations	5040	51.8%	4063	41.8%	627	6.4%	9730	100%
	Medium-risk occupations	6002	59.0%	3501	34.4%	670	6.6%	10,173	100%
	High-risk occupations	8832	61.9%	4453	31.2%	991	6.9%	14,276	100%
	Total	19,874	58.1%	12,017	35.2%	2288	6.7%	34,179	100%

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