Journal of Community & Applied Social Psychology

WILEY

RESEARCH ARTICLE OPEN ACCESS

Artificial Intelligence in the Workplace: Effects on Self-Efficacy, Self-Objectification and Beliefs in Free Will

Gabbiadini Alessandro | Durante Federica | Baldissarri Cristina | Manfredi Anna | Sterlicchio Antonio | Romano Sharon

Department of Psychology, Mind and Behavior Technological Center, University of Milano-Bicocca, Milano, Italy

Correspondence: Gabbiadini Alessandro (alessandro.gabbiadini@unimib.it)

Received: 10 January 2025 | **Revised:** 13 April 2025 | **Accepted:** 14 April 2025

Funding: The authors received no specific funding for this work.

Keywords: artificial intelligence | free will | self-efficacy | self-objectification

ABSTRACT

Artificial intelligence (AI) has increasingly integrated into daily life, with numerous industries adopting AI-driven systems to enhance services and automate repetitive tasks. The present work examines for the first time the short-term effects of interacting with an AI-based agent in the work domain on self-efficacy, self-objectification and beliefs in free will. In the first and second studies, scenarios describing the process of evaluating candidates for a job position were used to test the effects of interacting with an AI agent (vs. a human recruiter) on self-efficacy, self-objectification and beliefs in free will. In the third study, the experimental manipulation was carried out by adopting a real AI-based recruiting system to foster greater ecological validity. Findings consistently show that being evaluated by an AI recruiter (vs. a human recruiter) significantly lowers self-efficacy beliefs and increases self-objectification, leading, in turn, to a reduction in beliefs in free will. These results provide new insights into the workplace's self-objectification process, indicating how it might be triggered during interactions with modern AI technologies. Considerations on adopting AI technologies in the work domain are discussed, emphasising the need for AI systems to support, rather than replace, human agency.

1 | Introduction

Nowadays, technologies based on artificial intelligence (AI) are changing several aspects of our everyday life. The labour sector is one of the first areas to be affected by the revolution brought by AI (Johnson et al. 2021). As reported by several authors, the ongoing changes are not simply an extension of the Third Industrial Revolution but are increasingly recognised as a distinct Fourth Industrial Revolution by many economists, which is undeniably reshaping various facets of modern society (Schwab 2016). Productivity and behaviours implemented in the workplace and career paths are influenced and designed by Big Data analytics (Gati and Kulcsár 2021) and AI algorithms. The process of extracting and collecting data, particularly from human beings, has been recently termed datafication (Mayer-Schönberger and Cukier 2013; see also Southerton 2022). Different theoretical reflections state that this process involves quantifying phenomena and transforming them into data suitable for analysis (Mayer-Schönberger and Cukier 2013), leading individuals to perceive themselves as sources of extractable value, potentially activating self-objectification, namely, self-perception as mere objects or resources useful for other purposes (Sparascio et al. 2023).

In the present paper, we aim to provide the first empirical evidence that interacting with an AI algorithm that evaluates a human being as data, such as in the work context, may undermine individuals' self-perception as human beings having the ability to make free choices, within the theoretical framework of work objectification and self-objectification.

2 | Objectification and Self-Objectification

Objectification and self-objectification are manifestations of a broader phenomenon known as dehumanisation, by which specific individuals and social groups are perceived as objects or tools (Nussbaum 1995), denying individuals' humanity. When people are objectified, they are evaluated solely based on their usability and utility, effectively becoming instruments for others' purposes (Gruenfeld et al. 2008). Additionally, objectified individuals are attributed fewer mental states (Andrighetto et al. 2017). This process is strictly related to the insidious phenomenon of self-objectification, which occurs when individuals internalise this external objectifying perspective, leading them to view themselves more as instruments than as people (Calogero 2012). This issue permeates various aspects of social life, including the workplace, where it is referred to as work self-objectification (Baldissarri et al. 2014). Recent studies have found that self-objectification in the workplace can have specific consequences on individuals' beliefs in personal free will (e.g., Baldissarri et al. 2017, 2023).

Free will is a critical component of human identity, enabling individuals to pursue their interests within social contexts. It is considered an essential dimension of human existence, referring to the ability to make free and informed choices (Baumeister and Monroe 2014; Monroe and Malle 2010). Consequently, when individuals in an objectifying situation internalise this passive and dependent state, they can manifest a diminished sense of autonomy, reducing their belief in personal free will (Baldissarri et al. 2017). Two main factors contribute to fostering work self-objectification: the objectifying gaze adopted by individuals in power positions towards their subordinates and the specific characteristics of the work itself (Baldissarri et al. 2014). Additionally, certain work characteristics, such as 'repetitiveness, fragmentation, and other-direction (i.e., the external control of pace)' (Baldissarri et al. 2017, 251) can significantly affect the objectifying self-views of workers (Baldissarri et al. 2017).

In the present work, we propose that interacting with AI algorithms in work situations, such as job recruitment (where these tools are already common), can trigger self-objectification. This interaction may make individuals feel like objects, as mere data analysed by an algorithm (Sparascio et al. 2023). Specifically, interacting with AI can lower self-efficacy beliefs, with individuals depending on a pre-determined script set by the AI, fostering self-objectification and reducing beliefs in free will.

3 | Working Self-Objectification, Perceived Self-Efficacy and Free Will Beliefs

Over the past decade, psychological and philosophical literature has distinguished free will from other agency constructs, such as self-efficacy. Perceived self-efficacy refers to beliefs about one's ability to organise and perform actions to achieve specific performance levels (Bandura 1977, 1986, 1997). Individuals assess their chances of success based on how easy or difficult the required actions are (Ajzen 1991). Self-efficacy beliefs pertain to specific tasks and activities, reflecting individuals' perceptions of their capacity to perform those tasks within a given social context (Stajkovic and Luthans 1998). For example, individuals should have self-efficacy beliefs regarding their ability to find a new job, and research has shown that high levels of perceived self-efficacy during job searches are positively correlated with occupational outcomes (Caplan et al. 1989). On the contrary, studies indicate that low self-efficacy expectations significantly limit career choices (e.g., Betz and Hackett 1981). Generally, individuals lack a strong sense of personal efficacy in many work-related behaviours, preventing them from fully realising their potential in career pursuits (Betz and Hackett 1981; Beyer 2014). High self-efficacy beliefs are associated with a greater perception of control (Ajzen 1991), encompassing individuals' beliefs about their ability to manage factors that can facilitate or hinder the achievement of specific behavioural goals.

Belief in free will, instead, refers to the broad notion that human behaviour is not restricted by internal or external factors, allowing individuals to act freely across different situations, emphasising the capacity for choice and differentiating it from other constructs of agency (Feldman et al. 2014; Feldman 2017). People tend to link free will closely with the ability to make choices, which results in higher motivation and greater satisfaction with their decisions (Feldman et al. 2014). In contrast, self-efficacy focuses on the ability to execute tasks successfully and, unlike the belief in free will, it involves evaluating one's skills and abilities and considering whether one can achieve a particular goal. In this regard, Sappington (1990) pointed out that one can perceive oneself as incapable and still believe one is free to choose whether or not to take an action.

Building on prior research on workplace objectification and beliefs in free will (Baldissarri et al. 2017, 2019), we hypothesised that similar processes may arise when individuals face AI-made decisions. Since AI algorithms operate through predefined steps, people might find it harder to control situations managed by AI than those involving human interaction. As a result, individuals may feel their self-efficacy is diminished. Given self-efficacy's role in expressing human potential (Bandura and Wessels 1997), this could increase the perception of being object-like rather than fully human.

4 | Overview

We hypothesized that interacting with an AI algorithm during job recruitment may foster self-objectification by reducing the self-attribution of human mental states. Specifically, we expected that AI interaction would lower perceived control over tasks, diminishing self-efficacy, which would increase self-objectification and decrease beliefs in free will. To this aim, we conducted an initial pilot study to verify our hypotheses by adopting a written scenario. A formal study was then conducted by adopting similar written scenarios and confirming the emerging evidence. Finally, a second and more ecologically sound study was performed by employing a real AI-based system for the experimental manipulation.

All studies presented were conducted following ethical approval from the local Commission of the Department of Psychology for minimal-risk studies (Protocol Number RM-#2019215). Full informed consent was obtained from participants at the beginning of each study. Before performing the main analyses, exploratory factor analyses (EFA) were conducted for all the studies to verify the internal structure of the measures of interest. Based on the EFA results, the number of items retained for each scale in each study varied (results are fully reported in the Supporting Information).

5 | Pilot Study

5.1 | Method

5.1.1 | Participants and Procedures

Participants were recruited through snowball sampling by posting a web survey link on social media. One hundred and thirty-three volunteers completed the survey. We included one attention check item to obtain a reliable sample of respondents and identify participants who failed to pay close attention ('Please answer 2 to this question'; see Oppenheimer et al. 2009). We also included one manipulation check item ('The proposed scenario asked you to imagine an interview situation in which you interacted with an in-person recruiter/a system based on AI'). Four participants failed the attention check and one failed the manipulation check; therefore, they were excluded from the analyses. The analysed sample comprised 128 Italian participants (64 men, 64 women, $M_{age} = 32.86$, $SD_{age} = 10.61$; age range 22–78) and consisted of individuals with various educational qualifications: 3.1% had a middle school diploma, 3.1% had a professional diploma, 18.8% had a high school diploma, 27.3% held a bachelor's degree, 40.6% possessed a master's degree, 4.7% had a postgraduate master's degree, and 2.3% have a Ph.D.

The study was presented as research related to the perceptions of new technologies and would last about 10–15 min. Data were collected anonymously. Participants were randomly assigned to two experimental conditions after consenting to data processing for research purposes and completing some demographic items. Through a written scenario (see Supporting Information for the full description), participants in the first condition were asked to imagine having uploaded their CV for an open job position and then being interviewed by the HR manager of a fictitious company named STEMI. In the second condition, participants were asked to imagine applying for the same job. After uploading their CV, they were instructed to imagine also submitting a video where they introduced themselves, reflecting how this technology functioned at the time when we designed and carried out the studies. In this condition, participants were informed that the CV and video would be analysed by an AI agent capable of extracting information from both. In other words, the experimental condition differed from the control condition because it lacked interaction with a human being, which is replaced in the same tasks by an AI. In both conditions, participants were told that 1 week after the interview, they were informed that they had not obtained the job. After completing the survey, participants were debriefed and thanked.

5.2 | Measures

5.2.1 | Self-Efficacy Beliefs

An ad hoc scale was designed to measure self-efficacy beliefs (nine items). The following sentence introduced the scale: 'Now think about the selection process we just asked you to imagine. Regarding how the interview took place …' Sample items are '… I would be able to pursue my goals' and '… I would be in control of the events' and were anchored on a 7-point scale (1 = *strongly disagree*; 7 = *completely agree*).

5.2.2 | Self-Objectification

Self-objectification was operationalised using the self-mental state attribution task (SMSA; Haslam et al. 2008; Baldissarri et al. 2014, 2017). Participants were asked to rate (1 = *not at all*; 7 = *very much*) to what extent they felt they could experience 18 mental states during the imagined job interview. Mental states refer to perceptions (e.g., hearing), thoughts (e.g., reasoning), wishes (e.g., desiring), intentions (e.g., planning) and emotions (e.g., fear, pleasure). Lower scores indicate higher levels of self-objectification (for a similar approach, see Baldissarri et al. 2014, 2017).

5.2.3 | Beliefs in Personal Free Will

We adopted the personal free will subscale (eight items) from the free will and determinism scale (Rakos et al. 2008). Participants were required to indicate their beliefs in free will (1 = *not at all*; 7 = *extremely*) after imagining participating in the job selection. Sample items included 'I am in charge of my actions even when my life's circumstances are difficult', 'I actively choose what to do among the options I have', and 'I have free will'.

Moreover, as a possible control variable, participants were asked to report their level of technology familiarity, adopting a scale from 1 = *No familiarity* to 7 = *Complete familiarity*.

5.3 | Results

Composite scores for each scale were computed, and correlational analysis was performed on all our variables, considering also the control variable of familiarity with technology (see also the Supporting Information for the exploratory analyses specifically on the relationship between self-efficacy and free will measures). As shown in Table 1, self-efficacy was positively correlated with self-objectification and free will.

Since no significant correlation of technology familiarity emerged, this index was not entered into the following analysis. Separate ANOVAs (see Table 2) were conducted to examine the effect of the experimental condition (AI recruiter vs. human recruiter) on the dependent variables. When considering self-efficacy as the outcome, the analysis revealed a significant main effect of the experimental condition, $F(1,126) = 13.42$, $p < 0.001$, $\eta_p^2 = 0.096$, indicating that participants who were evaluated by an AI recruiter reported

TABLE 1 | Cronbach's alpha, means, standard deviations and correlations, pilot study.

	α	*M*	SD	1	2	3	4	5	6
1. Age	—	32.86	10.61	1					
2. Gender	—	—	—	−0.065	1				
3. Technology familiarity	—	—	—	−0.204*	−0.315***	1			
4. Self-efficacy	0.85	4.33	1.03	0.081	−0.177	0.153	1		
5. Self-objectification	0.89	4.92	0.95	−0.034	−0.103	0.109	0.568***	1	
6. Free will	0.90	5.20	1.15	0.085	−0.129	0.126	0.706***	0.584***	1

Note: $N=128$. Values for gender represent Spearman's correlation. *$p<0.05$, ***$p<0.001$.

significantly lower self-efficacy beliefs ($M=4.00$, $SD=1.13$) compared to those evaluated by a human recruiter ($M=4.65$, $SD=0.82$).

As for self-objectification, results indicated a significant effect of the experimental condition, $F(1,126)=5.57$, $p=0.020$, $\eta_p^2=0.042$, with participants in the AI recruiter condition ($M=5.11$, $SD=0.76$) reporting higher levels of self-objectification compared to those in the human recruiter condition ($M=4.72$, $SD=1.08$).

Finally, results revealed a significant main effect of the experimental condition on beliefs in free will, $F(1,126)=10.15$, $p=0.002$, $\eta_p^2=0.075$, indicating that participants who were evaluated by an AI recruiter ($M=4.88$, $SD=1.44$) reported significantly lower beliefs in free will compared to those who interacted with a human recruiter ($M=5.51$, $SD=0.65$).

To explore the prediction that being evaluated by an AI- (vs. human) recruiter would indirectly decrease individual beliefs in free will via self-efficacy and self-objectification, indirect effects were evaluated considering the joint significance of the components (Yzerbyt et al. 2018) and the bootstrap confidence intervals computed using the PROCESS macro for SPSS (v4.0, Model 6, 5000 iterations; Hayes 2017). Before running the analysis, given the strong correlation between self-efficacy and free will, we checked the collinearity between the variables by inspecting using the variance inflation factor (VIF). No collinearity emerged ($VIF=1.478$). We, therefore, included in the model the experimental condition as the focal predictor (1 = human recruiter, 2 = AI recruiter), self-efficacy and self-objectification as two serial mediators, and beliefs in free will as the outcome variable (see Table 2; Figure 1).

Results showed that even just imagining interacting with an AI agent for their evaluation affected the variables of interest. Participants reported lower self-efficacy, which was associated with an increase in self-objectification. Being evaluated by an AI agent (vs. human recruiter) indirectly decreased beliefs in free will via reduced self-efficacy and increased self-objectification.

6 | Discussion

The pilot study results indicate that self-efficacy plays a crucial role in promoting self-objectification and a reduction in beliefs in free will. In imagining interaction with an AI algorithm, participants may have perceived their actions as constrained by the algorithm's unknown choices, leading to a lower self-assessment of their agentive abilities. This limitation on possible actions might also diminish their belief in making independent choices, as the algorithm dictated the number of choices rather than their capabilities. Another interpretation is that self-efficacy could have been influenced by the general perception of AI algorithms as inflexible entities (Yigitcanlar et al. 2024).

Given this preliminary evidence, we conducted a new study to replicate and extend the pilot study. Because in the pilot study, participants were not selected for the job position in both experimental conditions, in Study 1, we tested whether the selection outcome could impact the dependent variables.

7 | Study 1

Study 1 aimed to more formally test the findings of the pilot study with a larger sample and rigorously examine whether the results were due to our manipulation or influenced by the job outcome. To address this, we introduced an additional manipulation by including positive and negative job outcomes. Therefore, the study involved a 2 (recruiter: HR recruiter vs. AI recruiter) × 2 (outcome: positive vs. negative) between-subjects design. Additionally, familiarity with technology measures was replaced with a more extensive scale for attitudes towards AI technologies.

7.1 | Method

7.1.1 | Participants and Procedures

To determine the sample size needed for the study, an a priori Monte Carlo power analysis for mediation models (Schoemann et al. 2017) was conducted. We considered a mediation model with two mediators, assuming a small-to-medium effect size (0.25; Cohen 2013) for all the paths (a1, b1, a2, b2) and a small-sized (0.20) effect between the two mediators (d) and for the direct effect (ca). The analysis suggested that $N=222$ is required to ensure a statistical power of at least 0.80 for detecting the indirect effects. As in the pilot study, participants were recruited through snowball sampling. Two hundred and thirty-six volunteers completed the survey. Adopting the same procedure used in the pilot study, 11 participants failed the attention and manipulation

TABLE 2 | Direct and indirect effects on individual beliefs in free will.

Predictors	Dependent variable	Direct and indirect components	Indirect effects	R^2
Model summary: $F(1,126)=13.42$, $p<0.001$				
Experimental condition	Self-efficacy	$b=-0.64$, SE $=0.17$, $t(126)=-3.66$, $p<0.001$, 95% CI [−0.98, −0.29]	—	0.09
Model summary: $F(2,125)=29.85$, $p<0.001$				
Experimental condition	Self-objectification	$b=-0.06$, SE $=0.14$, $t(125)=-0.42$, $p=0.673$, 95% CI [−0.35, 0.22]	—	0.32
Self-efficacy		$b=0.51$, SE $=0.07$, $t(125)=7.20$, $p<0.001$, 95% CI [0.37, 0.65]	—	
Model summary: $F(3,124)=50.64$, $p<0.001$				
Experimental condition	Free will	$b=-0.11$, SE $=0.14$, $t(124)=-0.80$, $p=0.422$, 95% CI [−0.40, 0.17]	—	0.55
Self-efficacy		$b=0.60$, SE $=0.08$, $t(124)=7.13$, $p<0.001$, 95% CI [0.43, 0.76]	—	
Self-objectification		$b=0.32$, SE $=0.09$, $t(124)=3.67$, $p<0.001$, 95% CI [0.15, 0.50]	—	
Experimental condition → self-efficacy → free will			**IE = −0.38, 95% CI [−0.66, −0.16]**	—
Experimental condition → self-objectification → free will			IE = −0.02, 95% CI [−0.13, 0.06]	—
Experimental condition → self-efficacy → self-objectification → free will			**IE = −0.10, 95% CI [−0.23, −0.02]**	—
Total effect			TE = −0.62, 95% CI [−1.01, −0.23]	—

Note: Unstandardised regression coefficients. Significant indirect effects are highlighted in bold.

checks and were excluded from the analyses. The final sample was then composed of 225 Italian participants (105 women, 116 men, 4 preferred not to answer, $M_{age}=27.39$, $SD_{age}=7.75$; age range 19–56; education level: 4.0% middle school diploma, 0.9% professional diploma, 45.3% high school diploma, 26.2% bachelor's degree, 16.4% master's degree, 6.7% postgraduate master's degree, 0.4% Ph.D). The employment status of the sample was as follows: 55.6% unemployed or still studying, 12.0% with a collaboration contract, 9.3% fixed-term employment contract, 15.1% permanent employment contract, 7.6% self-employed, and 0.4% business owner or entrepreneur. Participants were told that the study would last about 10–15 min. After completing the survey, participants were debriefed and thanked.

The experimental manipulation (i.e., scenarios) was identical to that used in the pilot study. The only difference was that half of the participants received a negative response (as in the pilot study), whereas the other half received a positive one (i.e., they were selected for the job).

7.2 | Measures

After collecting demographic variables and before presenting the experimental manipulation, attitudes towards AI were assessed by adapting a measure for attitudes towards automated systems (Jian et al. 2000; $\alpha=0.84$; 12 items; see also Supporting Information) to the AI context. Sample items are 'The results of an AI algorithm can be deceptive' and 'The results of an AI algorithm provide security'. The items were anchored on a 7-point scale (1 = *strongly disagree*, 7 = *completely agree*).

The remaining measures were the same as those used in the pilot study.

7.3 | Results

After the EFAs (see Supporting Information), we computed the composite score for each scale, and correlational analysis was performed on all our variables. As shown in Table 3, the same correlations observed in the pilot study emerged among the variables of interest.

Since attitudes towards AI technologies positively correlated with self-objectification, free will, and self-efficacy and participants' age was associated with attitudes, these variables were included as a covariate in the analyses of variance. Therefore, separate ANCOVAs (see Table 5) were conducted to examine the effects of selection outcome (passed vs. failed) and interviewer type (human recruiter vs. AI recruiter) on the dependent variables. The analysis revealed that interviewer type had significant effects on self-efficacy beliefs. Participants who were interviewed by a human examiner perceived more self-efficacy ($M=4.57$, $SD=1.00$) than those interviewed by an AI algorithm ($M=4.01$, $SD=1.07$), $F(1, 219)=16.64$, $p<0.001$, $\eta^2_p=0.071$. The interaction between selection outcome and interview type was not significant, $F(1,219)=3.52$, $p=0.062$, $\eta^2_p=0.016$. Moreover, attitudes towards AI were associated with self-efficacy, $F(1,219)=18.04$, $p<0.001$, $\eta^2_p=0.076$. However, age did not significantly predict self-efficacy, $F(1,219)=1.56$, $p=0.212$, $\eta^2_p=0.007$.

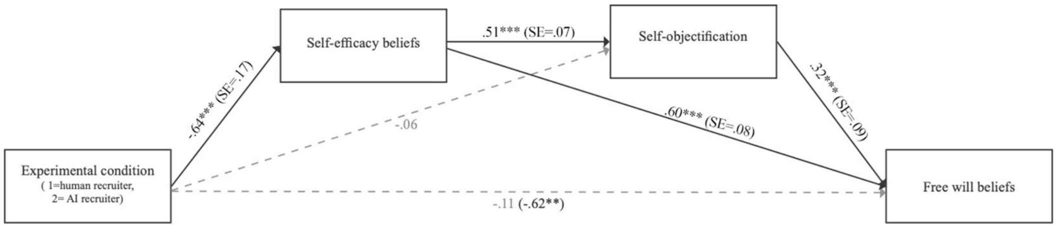

FIGURE 1 | Unstandardised regression coefficients for the indirect effects of the experimental condition on the belief in personal free will via self-efficacy and self-objectification for the pilot study. Self-objectification is expressed in terms of self-mental state attribution; lower levels indicate higher objectification. Dashed lines represent non-significant effects and bold lines significant effects. The total effect is in parentheses. $^{**}p \le 0.01$, $^{***}p \le 0.001$.

TABLE 3 | Cronbach's alpha, means, standard deviations and correlations for Study 1.

	α	M	SD	1	2	3	4	5	6
1. Age	—	27.39	7.75	1					
2. Gender	—	—	—	−0.071	1				
3. Self-efficacy	0.85	4.28	1.07	0.053	−0.085	1			
4. Self-objectification	0.87	5.01	0.86	0.039	−0.008	0.595***	1		
5. Free will	0.87	5.26	0.94	0.008	0.037	0.513***	0.598***	1	
6. Attitudes towards AI	0.86	4.42	0.86	−0.134*	−0.059	0.268***	0.147*	0.220***	1

Note: $N = 225$. Values for gender represent Spearman's correlation. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

For self-objectification, neither selection outcome, $F(1, 219) = 0.20$, $p = 0.652$, nor interview type, $F(1,219) = 2.66$, $p = 0.105$, significantly influenced experienced self-objectification. The interaction between selection outcome and interview type was also non-significant, $F(1, 219) = 0.41$, $p = 0.522$. Analyses, however, revealed a significant main effect of attitudes towards AI, $F(1,219) = 4.75$, $p = 0.030$, $\eta_p^2 = 0.021$, suggesting that positive attitudes towards AI were associated with lower perceptions of self-objectification. No effects were found for age, $F(1,219) = 0.56$, $p = 0.455$, $\eta_p^2 = 0.003$.

With regard to free will beliefs, the analysis revealed a significant main effect of interviewer type, $F(1,219) = 5.34$, $p = 0.022$, $\eta_p^2 = 0.024$, indicating that participants evaluated by an AI recruiter reported significantly lower beliefs in free will ($M = 5.12$, $SD = 1.04$) compared to those evaluated by a human recruiter ($M = 5.41$, $SD = 0.82$). The main effect of selection outcome was not significant, $F(1,219) = 2.70$, $p = 0.102$, $\eta_p^2 = 0.012$, suggesting that passing or failing the selection did not significantly impact beliefs in free will. The interaction effect between interviewer type and selection outcome was also not significant, $F(1,219) = 0.03$, $p = 0.871$, $\eta_p^2 = 0.000$. The ANOVA also revealed a significant main effect of attitudes on perceived free will, $F(1, 219) = 10.25$, $p = 0.002$, $\eta_p^2 = 0.045$, indicating that more positive AI attitudes were associated with greater perceptions of free will. No effects were found for participants' age, $F(1,219) = 0.11$, $p = 0.738$, $\eta_p^2 = 0.001$.

Once it was established that the outcome of the job selection (positive vs. negative) did not affect the dependent variables, as in the Pilot Study, we checked for collinearity (VIF = 1.739) and performed the same serial mediation model. Since the analysis of covariance did not reveal any significant effects of participants' age, this variable was not included in the model. However, attitudes towards AI were included as a control variable (see Table 4 and Figure 2).

Consistent with the pilot study, the results showed that participants reported lower self-efficacy, which was associated with increased self-objectification. Being evaluated by an AI agent (vs. human recruiter) indirectly decreased beliefs in free will via reduced self-efficacy and increased self-objectification.

7.4 | Discussion

Study 1 provided robust evidence regarding the psychological impacts of AI versus human recruiters on individuals' self-perception and beliefs in free will. In both the pilot study and Study 1, the type of recruiter (AI vs. human) significantly influenced self-efficacy, self-objectification, and free will beliefs, confirming our initial hypotheses.

The consistent association between self-efficacy and self-objectification across both studies highlights an interesting interplay between these constructs. The scenarios used may have promoted the perception that, if real, such interaction would be inherently imbalanced and other-directed—two typical features of objectifying activities (see Baldissarri et al. 2022)—with individuals providing data unilaterally to the AI agent. As a result, this process may have diminished participants' perception of control over the outcome of the job selection. The algorithm decisively determines whether the

TABLE 4 | Direct and indirect effects on individual beliefs in free will.

Predictors	Dependent variable	Direct and indirect components	Indirect effects	R^2
Model summary: $F(2,222) = 17.23$, $p < 0.001$				
Experimental condition	Self-efficacy	$b = -0.53$, SE = 0.13, $t(222) = -4.00$, $p < 0.001$, 95% CI [−0.79, −0.27]	—	0.13
Attitudes towards AI		$b = 0.32$, SE = 0.08, $t(222) = 4.13$, $p < 0.001$, 95% CI [0.16, 0.47]	—	
Model summary: $F(3,221) = 40.86$, $p < 0.001$				
Experimental condition	Self-objectification	$b = 0.07$, SE = 0.09, $t(221) = 0.82$, $p = 0.408$, 95% CI [−0.10, 0.26]	—	0.35
Self-efficacy		$b = 0.49$, SE = 0.04, $t(221) = 10.54$, $p < 0.001$, 95% CI [0.39, 0.58]	—	
Attitudes towards AI		$b = -0.01$, SE = 0.05, $t(221) = -0.27$, $p = 0.783$, 95% CI [−0.12, 0.95]	—	
Model summary: $F(4,220) = 37.66$, $p < 0.001$				
Experimental condition	Free will	$b = -0.09$, SE = 0.10, $t(220) = -0.91$, $p = 0.359$, 95% CI [−0.29, 0.11]	—	0.40
Self-efficacy		$b = 0.17$, SE = 0.06, $t(220) = 2.92$, $p = 0.004$, 95% CI [0.05, 0.29]	—	
Self-objectification		$b = 0.50$, SE = 0.07, $t(220) = 7.08$, $p < 0.001$, 95% CI [0.36, 0.64]	—	
Attitudes towards AI		$b = 0.11$, SE = 0.06, $t(220) = 1.80$, $p = 0.072$, 95% CI [−0.009, 0.22]		
Experimental condition → self-efficacy → free will beliefs			**IE = −0.09, 95% CI [−0.34, −0.04]**	—
Experimental condition → self-objectification → free will beliefs			IE = 0.04, 95% CI [−0.05, 0.13]	—
Experimental condition → self-efficacy → self-objectification → free will beliefs			**IE = −0.13, 95% CI [−0.21, −0.06]**	—
Total effect			TE = −0.28, 95% CI [−0.52, −0.04]	

Note: Unstandardised regression coefficients. Significant indirect effects are highlighted in bold.

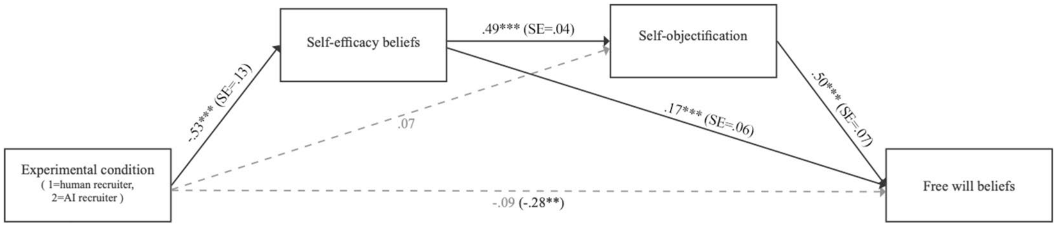

FIGURE 2 | Unstandardised regression coefficients for the indirect effects of the experimental condition on the belief in personal free will via self-efficacy and self-objectification for Study 1. Self-objectification is expressed in terms of self-mental state attribution; lower levels indicate higher objectification. Dashed lines represent non-significant effects and bold lines significant effects. The total effect is in parentheses. $^{**}p \leq 0.01$, $^{***}p \leq 0.001$.

candidate's responses align with preset evaluation parameters unknown to the user. Consequently, this imagined interaction with an AI agent may have reduced self-efficacy regarding the ability to execute tasks successfully. The results also show that lower self-efficacy scores were associated with higher levels of self-objectification, suggesting that individuals who feel less in control of the outcome also tend to attribute fewer mental states to themselves. It seems, therefore, that such a reduction in self-efficacy can foster two processes simultaneously: it can directly influence beliefs in free will (i.e., the ability to choose autonomously) and promote the internalisation of the algorithm's objectifying perspective in the form of datafication, leading to a decreased belief in making free choices. It is, therefore, possible that when individuals actively interact with a software agent based on AI models, they may internalise the algorithm's perspective, viewing themselves as a set of data to be processed. Interestingly, the outcome of the selection process (positive vs. negative) did not significantly affect the dependent variables. This suggests that the mere presence of an AI recruiter, regardless of the outcome, is sufficient to influence self-efficacy, self-objectification and free will beliefs.

Given these results, we replicated the findings in a second study using a more ecological experimental paradigm. In Study 2, a real AI-based chatbot for personnel selection was adopted.

8 | Study 2

Written scenarios were used as experimental manipulation in the pilot study and Study 1. This approach offers a good possibility for investigation, but it is ecologically limited. Additionally, recent work has shown that when faced with the outputs of different AI algorithms, individuals reported feeling threatened (Gabbiadini et al. 2024).

The existing literature about the perceived threat elicited by AI technologies is yet modest. However, recently Gabbiadini et al. (2024) reported in three studies that modern generative AI algorithms represent a realistic threat and a threat to human identity. Realistic threat refers to threats to the material resources, safety, and physical well-being of the ingroup, represented by the group of human beings. In HR recruitment, algorithms based on AI may be viewed as threatening to human jobs because of their ability to replace human activities, since the perception of being replaced by technologies can cause stress. On the other hand, human identity threat refers to those sources of threat—in this case, technological applications—which may affect ingroups' uniqueness, values and distinctiveness (Riek et al. 2006; Stephan et al. 1999).

Building on these considerations, Study 2 aims to overcome the limitations of the previous studies by (1) adopting a real AI-based conversational chatbot for job candidate screening and (2) preliminarily exploring the relationship between self-objectification and threat perceptions (i.e., realistic and human identity threats).

We employed a real chatbot based on an AI algorithm to promote greater ecological validity. The chatbot is a professional software provided by a commercial company operating in AI and customer relationship management. Hundreds of companies already widely use such a conversational pre-trained agent as a customer relationship maintenance agent and for pre-selecting candidates for open positions.

8.1 | Method

8.1.1 | Participants and Procedures

The model tested was the same as that described in Study 1. Therefore, we referred to the power analysis previously described (e.g., $N = 222$) to determine the sample size. As in the previous two studies, participants were recruited through snowball sampling. Personal contacts of research assistants were invited, asking them to indicate additional people to invite. Some participants were instead invited to participate in the experiment through the Department's Sona System recruitment platform in exchange for extra credits. Two hundred and eighty-one volunteers completed the survey. Sixty-two failed the manipulation checks, whereas one failed the attentional check (e.g., 'Please answer 2 to this question'). Therefore, these participants were excluded from the analyses. The final sample was then composed of 218 participants (132 women, 85 men, 1 preferred not to answer, $M_{age} = 31.95$, $SD_{age} = 10.84$; age range 18–64; 99% Italian, 0.5% Ivorian and 0.5% Ukraine). All participants were fluent in Italian. The educational levels of the sample were as follows: 4.1% middle school diploma, 2.8% professional diploma, 40.8% high school diploma, 23.4% bachelor's degree, 24.8% master's degree, 2.8% postgraduate master's degree, and 1.4% Ph.D. Regarding employment status, participants reported that 26.1% were currently unemployed or still studying, 7.8% had a collaboration contract, 16.1%

had a fixed-term employment contract, 40.4% with a permanent employment contract, 7.3% were self-employed, and 2.3% were business owners or entrepreneurs. Participants were told that the study would last about 60 min. After completing the survey, participants were debriefed and thanked.

As for the procedure, demographics and attitudes towards AI technologies were assessed after obtaining participants' consent and before presenting the experimental manipulation. Then, participants were randomly assigned to one of the two experimental conditions. After the experimental manipulation, self-efficacy, self-objectification, free will, realistic threat and human identity threat were assessed. Items for each scale were presented in a random order.

As in the previous studies, participants were asked to imagine applying for a job interview for a fictitious STEMI company. Participants were then invited to explore the company website, which displayed a banner on the home page suggesting open job positions. They were then invited to apply to the job call by interacting through the chat system provided by the website. Since in Study 1 the selection outcome (positive or negative) had no effects on the outcome variables, in Study 2 we maintained only two experimental conditions and provided the negative feedback as in the Pilot Study. In one condition, the chat system was operated by an AI agent, while in the other, the interaction occurred with a real person.

Data collection was conducted online, with appointments scheduled through video calls. During the experimental session, a research assistant sent participants a link to the dummy STEMI website. After exploring the web page, participants were invited to access the chat system. Depending on their assigned condition, participants were informed that they would be interviewing with an AI recruiter or a human recruiter. The research assistant disconnected from the video call, allowing participants to interact freely through the prearranged chat. In the AI recruiter condition, the conversation was guided by the algorithm. In the control condition, the research assistant interacted with the participant. In both conditions, the algorithm and the human operator followed the same script (see the Supporting Information for the full script), although some deviations due to potential variability in participant responses and requests might have occurred. In these cases, the chatbot and the operator were instructed to bring the conversation back to the job interview. For instance, if participants answered irrelevantly to the question 'what were your previous occupations?' both the chatbot and the research assistants were instructed to remind participants to stick to the question asked.

The chatbot was based on a natural language processing algorithm trained to develop a set of candidate evaluation questions and to understand and generate responses to user inputs in the specific context of a job interview. Indeed, the AI agent was trained on specific entities and utterances. Entities represent specific pieces of information or data within a user's input. They are used to extract relevant details from user messages to understand their intent or context better. Utterances are individual statements or messages exchanged between users and the chatbot. They can be questions, commands, greetings, or any other form of communication and serve as inputs to the chatbot's natural language understanding module, which processes them to determine the user's intent and extract relevant entities.

On average, the interview lasted about 40 min. Both the chatbot and the human operator concluded the interview by telling the candidate to wait a few minutes to get the outcome of the pre-selection interview, and the participants were told that the outcome was unsuccessful.

8.2 | Measures

Self-efficacy, self-objectification, free will beliefs and attitudes towards AI were assessed. Additionally, participants completed a scale to measure the extent to which they perceived AI to pose a realistic threat (five items) and a threat to human identity (five items; EFA results for all the scales are reported in the Supporting Information). These items were adapted from previous research targeting robots (Yogeeswaran et al. 2016; Złotowski et al. 2017) and have already been used in previous work on the perception of generative AI (Gabbiadini et al. 2024). Sample items included: 'Advancements in AI technology threaten human employment and opportunities' and 'In the long run, AI poses a direct threat to human safety and wellbeing', anchored on a 7-point scale (1 = *strongly disagree*, 7 = *completely agree*; see Supporting Information for EFA analysis).

8.3 | Results

After checking for the scales' structure, composite scores for each scale were computed, and correlational analysis was performed on all the considered variables (see Table 5). As in Study 1, attitudes towards AI were entered as a controlling variable in all the following analyses.

Therefore, separate ANCOVAs were conducted to examine the effects of interviewer type (HR chat vs. AI chat), considering attitudes towards AI as a controlling variable. The analysis revealed a significant main effect of interviewer type, $F(1,215) = 4.51$, $p = 0.035$, $\eta_p^{\ 2} = 0.021$, indicating that participants interacting with an AI chatbot reported lower self-efficacy ($M = 3.92$, SD = 1.29) compared to those who interacted with a human recruiter chatbot ($M = 4.30$, SD = 0.96). Moreover, analyses revealed a significant main effect of attitudes towards AI on self-efficacy, $F(1, 215) = 26.63$, $p < 0.001$, $\eta^2_{\ p} = 0.110$, indicating that more positive attitudes towards AI were associated with greater self-efficacy.

When considering self-objectification as the outcome, the results revealed a significant main effect of interviewer type, $F(1,215) = 24.61$, $p < 0.001$, $\eta_p^{\ 2} = 0.103$, with participants in the AI chatbot condition ($M = 3.70$, SD = 1.02) reporting higher self-objectification than those in the HR chatbot condition ($M = 4.39$, SD = 0.95). However, attitudes did not significantly predict self-objectification, $F(1, 215) = 2.72$, $p = 0.101$.

TABLE 5 | Cronbach's alpha, means, standard deviations and correlations, Study 2.

	α	M	SD	1	2	3	4	5	6	7	8
1. Age	—	31.99	10.83	1							
2. Gender	—	—	—	0.017	1						
3. Self-efficacy	0.88	4.12	1.14	0.031	−0.043	1					
4. Self-objectification	0.89	4.06	1.04	0.018	0.107	0.439***	1				
5. Free will	0.92	4.97	1.27	0.010	0.075	0.659***	0.449***	1			
6. Attitudes towards AI	0.87	4.47	0.93	−0.097	0.107	0.341***	0.135**	0.407***	1		
7. Realistic threat	0.71	4.13	1.31	−0.005	0.023	−0.285***	−0.267***	−0.268***	−0.215***	1	
8. Human identity threat	0.87	3.56	1.43	0.130	0.117	−0.326***	−0.165*	−0.374***	−0.400**	0.534***	1

Note: $N=218$. Values for gender represent Spearman's correlation. *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$.

With regard to realistic threat, results indicated a significant main effect of interviewer type, $F(1,215)=4.33$, $p=0.039$, $\eta_p^2=0.020$, with AI-based recruiter interactions associated with higher perceived realistic threat ($M=4.34$, $SD=1.33$) compared to the human recruiter interactions ($M=3.93$, $SD=1.26$). Moreover, AI attitudes were negatively associated with perceived realistic threat, $F(1, 215)=9.31$, $p=0.003$, $\eta_p^2=0.042$, indicating that positive attitudes towards AI were linked to lower perceptions of realistic threat.

As for human identity threat, the results showed a non-significant effect of interviewer type, $F(1,215)=1.06$, $p=0.304$, $\eta_p^2=0.005$, indicating that the type of interviewer (AI chatbot vs. HR chatbot) did not significantly influence perceptions of human threat (respectively, $M=3.71$, $SD=1.46$ and $M=3.43$, $SD=1.40$). Attitudes towards AI had an effect instead, $F(1, 215)=39.60$, $p<0.001$, $\eta_p^2=0.156$, suggesting that positive attitudes towards AI were associated with lower perceptions of human threat.

Last, we examined the effects of interviewer type on beliefs in free will. The analysis revealed a significant main effect of interviewer type, $F(1,215)=16.18$, $p<0.001$, $\eta_p^2=0.070$, with AI chatbot interactions associated with lower beliefs in free will ($M=4.60$, $SD=1.54$) than HR chatbot interactions ($M=5.31$, $SD=0.84$). Attitudes also had a significant positive effect, $F(1, 215)=40.65$, $p<0.001$, $\eta_p^2=0.159$, indicating that participants with positive attitudes towards AI reported higher levels of free will.

No collinearity between self-efficacy and free will was detected ($VIF=1.375$). Therefore, we tested the same model reported in the previous studies (see Table 6; Figure 3; for additional exploratory models that also include threat perception as a possible mediator, see Table S13 and Figure S3).[1]

Results showed the same pattern of results found in the previous studies, although here we found a partial mediation between the experimental manipulation and free will beliefs.

8.4 | Discussion

Study 2 aimed to replicate the results found in the previous studies by adopting a more ecologically valid paradigm (i.e., real AI-based agents for job interviews). Consistent with our hypotheses, the multivariate variance analyses confirmed that the type of recruiter (human vs. AI) significantly impacted participants' self-efficacy beliefs, self-objectification, beliefs in free will, and perceptions of realistic threats posed by AI. However, no significant effects were found on the perceived threat to human identity.

Additionally, the effect of the experimental condition on free will, differently from the previous studies, was only partially mediated by self-efficacy and self-objectification. Previous research suggests that belief in free will is understood as the idea that people can act freely without external constraints (Feldman 2017; Kane 2011), perceiving that alternative options are available (Nichols 2004). In the first two studies, we used written scenarios for experimental manipulation. However, in Study 2, we implemented a more realistic approach by having participants engage with a real AI recruiter over an extended period. This prolonged interaction likely made the constraints imposed during the interview more salient.

Another difference in the Study 2 results is that the experimental condition directly affected self-objectification. This result may be attributed to the fact that, in this study, participants were asked to undergo a real job selection process by interacting with an actual AI-based chatbot rather than imagining this situation through a written scenario. It could be that during the interactions with the chatbot, individuals could feel treated as a dataset to be analysed, thereby fostering objectification processes that were then internalised. Future studies could verify this interpretation in detail.

Finally, the significant role of attitudes towards AI in predicting self-efficacy and free will beliefs underscores the importance of individual predispositions in shaping responses to AI. Participants with more positive attitudes towards AI generally

TABLE 6 | Direct and indirect effects on individual beliefs in free will.

Predictors	Dependent variable	Direct and indirect components	Indirect effects	R^2
Model summary: $F(2,215) = 16.70$, $p < 0.001$				
Experimental condition	Self-efficacy	$b = -0.31$, SE = 0.14, $t(215) = -2.12$, $p = 0.034$, 95% CI [−0.59, −0.02]	—	0.13
Attitudes towards AI		$b = 0.40$, SE = 0.08, $t(215) = 5.16$, $p < 0.001$, 95% CI [0.25, 0.55]	—	
Model summary: $F(3,214) = 25.14$, $p < 0.001$				
Experimental condition	Self-objectification	$b = -0.55$, SE = 0.12, $t(214) = -4.42$, $p < 0.001$, 95% CI [−0.80, −0.30]	—	0.26
Self-efficacy		$b = 0.36$, SE = 0.05, $t(214) = 6.40$, $p < 0.001$, 95% CI [0.25, 0.48]	—	
Attitudes towards AI		$b = -0.03$, SE = 0.07, $t(214) = -0.43$, $p = 0.666$, 95% CI [−0.17, 0.11]	—	
Model summary: $F(4,213) = 57.37$, $p < 0.001$				
Experimental condition	Free will	$b = -0.31$, SE = 0.13, $t(213) = -2.45$, $p = 0.015$, 95% CI [−0.57, −0.06]	—	0.52
Self-efficacy		$b = 0.55$, SE = 0.06, $t(213) = 8.94$, $p < 0.001$, 95% CI [0.43, 0.68]	—	
Self-objectification		$b = 0.20$, SE = 0.07, $t(213) = 2.93$, $p = 0.003$, 95% CI [0.06, 0.33]	—	
Attitudes towards AI		$b = 0.28$, SE = 0.07, $t(213) = 4.02$, $p > 0.001$, 95% CI [0.14, 0.41]		
Experimental condition → self-efficacy → free will beliefs			**IE = −0.17, 95% CI [−033, −0.01]**	—
Experimental condition → self-objectification → free will beliefs			**IE = −0.11, 95% CI [−0.21, −0.03]**	—
Experimental condition → self-efficacy → self-objectification → free will beliefs			**IE = −0.02, 95% CI [−0.05, −0.001]**	—
Total effect			TE = −0.30, 95% CI [−0.52, −0.11]	

Note: Unstandardised regression coefficients. Significant indirect effects are highlighted in bold.

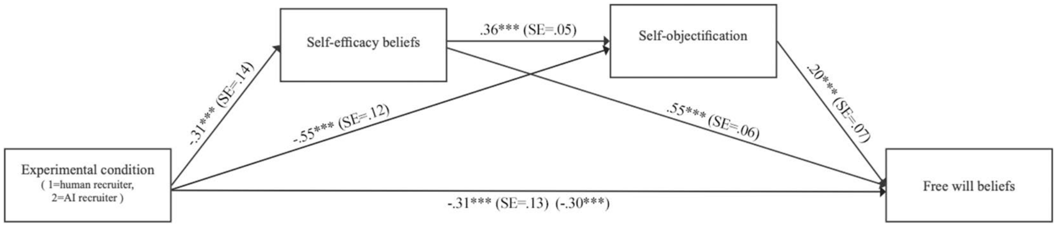

FIGURE 3 | Unstandardised regression coefficients for the indirect effects of the experimental condition on the belief in personal free will via self-efficacy and self-objectification for Study 2. Self-objectification is expressed in terms of self-mental state attribution; lower levels indicate higher objectification. Dashed lines represent non-significant effects and bold lines significant effects. The total effect is in parentheses. ***$p \leq 0.001$.

reported higher self-efficacy and lower perceptions of threat, indicating that fostering positive attitudes towards AI could mitigate some negative impacts of interacting with an AI agent. In this regard, to foster a smoother adoption of AI technologies, future studies should investigate the role of attitudes and trust in algorithms concerning negative perceptions of the human–AI relationship.

9 | General Discussion

The current research examined the psychological impacts of interacting with AI-based agents in a work-related context for the first time. As AI technologies are increasingly integrated into various productive sectors and everyday life, AI-based agents have become commonplace in many work environments. Thus, examining the potential psychological effects of these interactions is crucial. Current findings contribute a novel perspective to the literature on psychological well-being in the workplace, providing the first empirical evidence of the psychological effects that the introduction of AI in the workplace may cause. Across three studies, findings consistently indicate that interacting with an AI-based chatbot during a job interview significantly decreases perceived self-efficacy that, in turn, increases self-objectification and reduces beliefs in personal free will.

Moreover, we confirmed previous studies (Gabbiadini et al. 2024) showing that interacting with AI-based chatbots can elicit perceptions of realistic threats posed by AI technologies.

In the Pilot Study, participants who imagined interacting with an AI recruiter reported lower self-efficacy and higher self-objectification than those interacting with a human recruiter, leading to diminished beliefs in free will. Study 1 confirmed these findings and included recruitment outcomes (positive or negative), showing that the recruiter type (AI vs. human) significantly influenced self-efficacy, self-objectification, and free will beliefs, regardless of the outcome. Study 2 replicated these results in a real AI-based chatbot interaction, with participants reporting lower self-efficacy, higher self-objectification, and reduced free will beliefs in the AI condition.

It is worth noticing that self-efficacy and beliefs in free will were strongly correlated in all three studies. However, despite this association, the two constructs remain theoretically and empirically distinct (see Feldman 2017; see also the Supporting Information). Research suggests that individuals with higher self-efficacy perceive themselves as more capable of influencing their environment, which in turn strengthens their belief in free will (Stillman et al. 2010). Conversely, when self-efficacy is diminished—particularly in contexts where external constraints are emphasised—individuals may experience a reduced sense of free will, perceiving their actions as being determined by external forces rather than personal choice (Carey and Paulhus 2013).

In this regard, we found that interacting with an AI algorithm during a job interview reduced perceptions of self-efficacy, directly diminishing the sense of freedom in decision-making without necessarily inducing self-objectification (i.e., feeling treated as mere data to be analysed). One possible explanation for this effect is the absence of nonverbal cues, which are essential for guiding social interactions. Nonverbal signals help individuals determine appropriate behaviour and interpret others' reactions, and their absence can undermine a sense of agency in the interaction (Hall et al. 2019). Therefore, future research should further explore the role of self-efficacy in interactions with AI agents in the workplace—for instance, by replicating these findings using AI-driven digital humans or artificial human-like AI systems that are virtual entities designed to mimic human appearance, speech,= and behaviour in interactive settings.

Additionally, Study 2 explored perceptions of AI-induced threats. Participants interacting with the AI recruiter perceived a higher realistic threat to human employment and safety but did not view AI as a significant threat to human identity. This highlights the perception that AI agents could be seen as a practical and economic threat. Future studies should explore more deeply how the perception of threats influences self-objectification. For example, seeing an algorithm replace a human worker might initially be considered a threat, raising concerns about job security and financial stability. This perception could, in turn, lead to a diminished belief in personal agency. Similarly, when AI algorithms take over roles once played by humans, it may blur the distinction between what is uniquely human and what is merely software (Gabbiadini et al. 2024), thereby promoting increased self-objectification.

While AI has the potential to increase efficiency and productivity, it is important to understand how people will relate to these AI agents that could become real co-workers and what psychological reactions people can have when they are required to interact or even to be evaluated by an AI algorithm. Across all three studies, a consistent pattern emerged: AI-based recruitment processes undermine self-efficacy, increase self-objectification and reduce beliefs in personal free will. These findings align with the broader literature on objectification and self-objectification, suggesting that interactions with AI can lead individuals to perceive themselves as mere instruments or data points rather than autonomous agents.

In this regard, Montague and Matson (1983) identified technology as one of the principal motors of the dehumanisation process—of which objectification is a part—defining this phenomenon as 'technological dehumanisation'. Indeed, our results show that interacting with emerging AI-based agents entails a lower perception of self-efficacy. We speculate that when individuals interact with a software agent, they perceive less control over the situation compared to performing the same task interacting with another human being. This perception, combined with the awareness that an algorithm procedurally evaluates personal data (e.g., analysing their curriculum vitae and the words used during the video/interview) without creating an empathetic relationship, might explain the increase in self-objectification levels. In other words, we speculate that the *datafying* gaze of the algorithm could be internalised by people who could perceive themselves more as a database for processing rather than persons. Consistent with previous research (Baldissarri et al. 2017), this process has significant consequences, such as decreased beliefs in free will. Indeed, free will beliefs pertain to the extent to which individuals believe they control their actions and decisions. High free will beliefs are associated with personal autonomy and responsibility, while low free will beliefs suggest that external forces or predetermined factors dictate behaviour. The interaction between self-objectification and free will beliefs could influence various workplace behaviours and outcomes. For example, employees who feel less autonomous and more objectified might exhibit lower job satisfaction, lower creativity and worse overall well-being (for a review, see Baldissarri et al. 2022).

The perception of AI as a realistic threat, particularly regarding employment and safety, highlights another critical aspect of interacting with an AI-based agent. As AI technologies advance and become more integrated into various aspects of society, concerns about their impact on job security and economic well-being are growing. We speculate that the perception of threat can exacerbate feelings of objectification and further diminish self-efficacy and free will beliefs (see Table S16 and Figure S3). This result is further supported by the effects of individuals' attitudes towards AI technologies. Findings from Studies 1 and 2 suggest that more positive attitudes towards AI are associated with fewer negative consequences, such as lower levels of self-objectification and stronger beliefs in free will. This aligns with the growing need to enhance public understanding of AI technologies, emphasising the importance of improving technology literacy to foster more informed and balanced perceptions of these systems.

The present findings enhance our understanding of the psychological impacts of AI interactions, emphasising the importance of carefully managing the human–AI relationships in organisational settings. Organisations should be mindful of the potential to undermine self-efficacy and increase self-objectification. To mitigate these effects, AI systems should be designed as a support tools for human recruiters rather than replacing them, preserving the benefits of AI while maintaining meaningful human interactions.

9.1 | Limitations and Future Directions

As with all research, the present work has some limitations that should be considered when interpreting the results. Indeed, we considered a measure of self-objectification that focuses on the reduction of perception of the mental states that define us as humans. Future studies should consider more specific measures to support the idea that interacting with AI can generate dehumanisation in the form of datafication. Moreover, research should deepen the role of possible individual differences affecting human self-perception when interacting with AI-based systems, such as familiarity with AI and personality traits.

Future research should explore interventions to enhance self-efficacy and reduce self-objectification in AI-mediated interactions. For example, providing individuals with more control over the interaction or incorporating human elements into the AI system may help to mitigate the negative impacts observed in this research. Indeed, our results are based on a single interaction with an AI agent, so the observed effects might only be short-term. Future studies should consider a longitudinal experimental design to explore the impact of continuous, long-term interactions with an AI algorithm. Longitudinal studies could also provide deeper insights into the long-term effects of AI interactions on personal and societal beliefs, helping to inform the development of more humane and supportive AI systems.

In this regard, the human–AI interaction (HAI) research area is emerging as a key field, focusing on designing and evaluating interactions between humans and AI systems by considering individual factors that enhance user experience with AI and the social impacts of such interactions. As AI technologies advance, it becomes crucial to understand and mitigate potential negative effects on individuals' perceptions and beliefs.

10 | Conclusion

AI is transforming the workplace with significant potential benefits, but it is also seen as a major risk when used in decision-making (Araujo et al. 2020; Gabbiadini et al. 2024). Therefore, it is essential to consider human factors and psychological dynamics in AI interactions. In line with the European Commission's Industry 5.0 vision (European Commission 2021), AI systems should adopt a sustainable, human-centric approach, prioritising user needs. This calls for a shift towards Augmented Intelligence, where AI enhances rather than replaces human skills, complementing and amplifying human decision-making and performance.

While AI offers significant advantages in optimising work tasks, companies must implement it thoughtfully. This necessitates a balance between technological adoption in the workplace and systems that can adapt to people's needs, such as adopting a hybrid model that integrates the strengths of AI and human factors.

Author Contributions

G.A.: conceptualisation, methodology, writing – original draft, formal analysis. **D.F.:** conceptualisation, writing – review and editing. **B.C.:** writing – review and editing. **M.A.:** data collection, writing – review and editing. **S.A.:** writing – review and editing. **R.S.:** writing – review and editing.

Acknowledgements

During the preparation of this work, the authors used ChatGPT in order to improve the text's fluency in English and check for grammatical errors. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the publication's content. Open access publishing facilitated by Universita degli Studi di Milano-Bicocca, as part of the Wiley - CRUI-CARE agreement.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available on Open Science Framework at https://osf.io/ps2rw/?view_only=c9674fadd2394e80bb8bc386cb089fde.

Endnotes

[1] Given the significant role of attitudes in predicting self-efficacy and beliefs in free will, a conditional serial mediation model was also tested, in which the attitudes toward AI were considered as the moderating variable (PROCESS macro, model 85). No significant interactions emerged (all $p > 0.06$). Therefore, for parsimony, attitudes were considered as a covariate.

References

Ajzen, I. 1991. "The Theory of Planned Behavior." *Organizational Behavior and Human Decision Processes* 50: 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.

Andrighetto, L., C. Baldissarri, and C. Volpato. 2017. "(Still) Modern Times: Objectification at Work." *European Journal of Social Psychology* 47, no. 1: 25–35. https://doi.org/10.1002/ejsp.2190.

Araujo, T., N. Helberger, S. Kruikemeier, and C. H. De Vreese. 2020. "In AI We Trust? Perceptions About Automated Decision-Making by Artificial Intelligence." *AI & Society* 35, no. 3: 611–623. https://doi.org/10.1007/s00146-019-00931-w.

Baldissarri, C., L. Andrighetto, A. Gabbiadini, and C. Volpato. 2017. "Work and Freedom? Working Self-Objectification and Belief in Personal Free Will." *British Journal of Social Psychology* 56, no. 2: 250–269. https://doi.org/10.1111/bjso.12172.

Baldissarri, C., L. Andrighetto, and C. Volpato. 2014. "When Work Does Not Ennoble Man: Psychological Consequences of Working Objectification." *TPM: Testing, Psychometrics, Methodology in Applied Psychology* 21, no. 3: 327–339. https://doi.org/10.4473/TPM21.3.7.

Baldissarri, C., L. Andrighetto, and C. Volpato. 2019. "Feeling Like an Object: A Field Study on Working Self-Objectification and Belief in Personal Free Will." *TPM: Testing, Psychometrics, Methodology in Applied Psychology* 26, no. 2: 185–197. https://doi.org/10.4473/TPM26.2.1.

Baldissarri, C., L. Andrighetto, and C. Volpato. 2022. "The Longstanding View of Workers as Objects: Antecedents and Consequences of Working Objectification." *European Review of Social Psychology* 33, no. 1: 81–130. https://doi.org/10.1080/10463283.2021.1956778.

Baldissarri, C., S. Pagliaro, M. Teresi, and L. Andrighetto. 2023. "Humanness in Times of Uncertainty: On the Link Between Perceived Job Insecurity, Self-Objectification and Well-Being." *European Journal of Social Psychology* 53, no. 1: 195–211. https://doi.org/10.1002/ejsp.2897.

Bandura, A. 1977. "Self-Efficacy: Toward a Unifying Theory of Behavioral Change." *Psychological Review* 84: 191–215. https://doi.org/10.1037/0033-295X.84.2.191.

Bandura, A. 1986. *Social Foundations of Thought and Action: A Social Cognitive Theory*. Prentice-Hall.

Bandura, A. 1997. *Self-Efficacy: The Exercise of Control*. Freeman.

Bandura, A., and S. Wessels. 1997. "Self-Efficacy." In *Thinking Critically About Psychological Science*, edited by D. Halpern, 4–6. Cambridge University Press.

Baumeister, R. F., and A. E. Monroe. 2014. "Recent Research on Free Will: Conceptualizations, Beliefs, and Processes." *Advances in Experimental Social Psychology* 50: 1–52. https://doi.org/10.1016/B978-0-12-800284-1.00001-1.

Betz, N. E., and G. Hackett. 1981. "The Relationship of Career-Related Self-Efficacy Expectations to Perceived Career Options in College Women and Men." *Journal of Counseling Psychology* 28, no. 5: 399–410. https://doi.org/10.1037/0022-0167.28.5.399.

Beyer, S. 2014. "Why Are Women Underrepresented in Computer Science? Gender Differences in Stereotypes, Self-Efficacy, Values, and Interests and Predictors of Future CS Course-Taking and Grades." *Computer Science Education* 24, no. 2: 153–192. https://doi.org/10.1080/08993408.2014.963363.

Calogero, R. M. 2012. "Objectification Theory, Self-Objectification, and Body Image." In *Body Image: A Handbook of Science, Practice, and Prevention*, edited by T. F. Cash and L. Smolak. Guilford Press. https://doi.org/10.1016/B978-0-12-384925-0.00091-2.

Caplan, R. D., A. D. Vinokur, R. H. Price, and M. Van Ryn. 1989. "Job Seeking, Reemployment, and Mental Health: A Randomized Field Experiment in Coping With Job Loss." *Journal of Applied Psychology* 74, no. 5: 759–769. https://doi.org/10.1037/0021-9010.74.5.759.

Carey, J., and D. L. Paulhus. 2013. "Worldview Implications of Belief in Free Will and Determinism: Politicization and Punitiveness." *Journal of Personality and Social Psychology* 104, no. 3: 446–463. https://doi.org/10.1111/j.1467-6494.2012.00799.x.

Cohen, J. 2013. *Statistical Power Analysis for the Behavioral Sciences*. 2nd ed. Routledge. https://doi.org/10.4324/9780203771587.

European Commission. 2021. "Industry 5.0, a Transformative Vision for Europe—Governing Systemic Transformations Towards a Sustainable Industry. Publications Office of the European Union." https://doi.org/10.2777/17322.

Feldman, G. 2017. "Making Sense of Agency: Belief in Free Will as a Unique and Important Construct." *Social and Personality Psychology Compass* 11, no. 1: e12293. https://doi.org/10.1111/spc3.12293.

Feldman, G., R. F. Baumeister, and K. F. E. Wong. 2014. "Free Will Is About Choosing: The Link Between Choice and the Belief in Free Will." *Journal of Experimental Social Psychology* 55: 239–245. https://doi.org/10.1016/j.jesp.2014.07.012.

Gabbiadini, A., D. Ognibene, C. Baldissarri, and A. Manfredi. 2024. "The Emotional Impact of Generative AI: Negative Emotions and Perception of Threat." *Behaviour & Information Technology* 44, no. 4: 1–18. https://doi.org/10.1080/0144929X.2024.2333933.

Gati, I., and V. Kulcsár. 2021. "Making Better Career Decisions: From Challenges to Opportunities." *Journal of Vocational Behavior* 126: 103545. https://doi.org/10.1016/j.jvb.2021.103545.

Gruenfeld, D. H., M. E. Inesi, J. C. Magee, and A. D. Galinsky. 2008. "Power and the Objectification of Social Targets." *Journal of Personality* and Social Psychology 95, no. 1: 111–127. https://doi.org/10.1037/0022-3514.95.1.111.

Hall, J. A., T. G. Horgan, and N. A. Murphy. 2019. "Nonverbal Communication." *Annual Review of Psychology* 70, no. 1: 271–294. https://doi.org/10.1146/annurev-psych-010418-103145.

Haslam, N., S. Loughnan, Y. Kashima, and P. Bain. 2008. "Attributing and Denying Humanness to Others." *European Review of Social Psychology* 19, no. 1: 55–85. https://doi.org/10.1080/10463280801981645.

Hayes, A. F. 2017. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. Guilford Publications.

Jian, J. Y., A. M. Bisantz, and C. G. Drury. 2000. "Foundations for an Empirically Determined Scale of Trust in Automated Systems." *International Journal of Cognitive Ergonomics* 4, no. 1: 53–71. https://doi.org/10.1207/S15327566IJCE0401_04.

Johnson, M., R. Jain, P. Brennan-Tonetta, et al. 2021. "Impact of Big Data and Artificial Intelligence on Industry: Developing a Workforce Roadmap for a Data-Driven Economy." *Global Journal of Flexible Systems Management* 22, no. 3: 197–217. https://doi.org/10.1007/s40171-021-00272-y.

Kane, R. 2011. *The Oxford Handbook of Free Will*. Oxford University Press.

Mayer-Schönberger, V., and K. Cukier. 2013. *Big Data: A Revolution That Will Transform How We Live, Work, and Think*. Houghton Mifflin Harcourt.

Monroe, A. E., and B. F. Malle. 2010. "From Uncaused Will to Conscious Choice: The Need to Study, Not Speculate About People's Folk Concept of Free Will." *Review of Philosophy and Psychology* 1, no. 2: 211–224. https://doi.org/10.1007/s13164-009-0010-7.

Montague, A., and F. Matson. 1983. *The Dehumanization of Man*. McGraw-Hill.

Nichols, S. 2004. "The Folk Psychology of Free Will: Fits and Starts." *Mind & Language* 19, no. 5: 473–502. https://doi.org/10.1111/j.0268-1064.2004.00269.x.

Nussbaum, M. 1995. "Objectification." *Philosophy & Public Affairs* 24, no. 4: 249–291. https://doi.org/10.1111/j.1088-4963.1995.tb00032.x.

Oppenheimer, D. M., T. Meyvis, and N. Davidenko. 2009. "Instructional Manipulation Checks: Detecting Satisficing to Increase Statistical Power." *Journal of Experimental Social Psychology* 45, no. 4: 867–872. https://doi.org/10.1016/j.jesp.2009.03.009.

Rakos, R. F., K. R. Laurene, S. Skala, and S. Slane. 2008. "Belief in Free Will: Measurement and Conceptualization Innovations." *Behavior and Social Issues* 17: 20–40. https://doi.org/10.5210/bsi.v17i1.1929.

Riek, B. M., E. W. Mania, and S. L. Gaertner. 2006. "Intergroup Threat and Outgroup Attitudes: A Meta-Analytic Review." *Personality and Social Psychology Review* 10, no. 4: 336–353. https://doi.org/10.1207/s15327957pspr1004_4.

Sappington, A. A. 1990. "Recent Psychological Approaches to the Free Will Versus Determinism Issue." *Psychological Bulletin* 108, no. 1: 19–29. https://doi.org/10.1037/0033-2909.108.1.19.

Schoemann, A. M., A. J. Boulton, and S. D. Short. 2017. "Determining Power and Sample Size for Simple and Complex Mediation Models." *Social Psychological and Personality Science* 8, no. 4: 379–386. https://doi.org/10.1177/1948550617715068.

Schwab, K. 2016. *The Fourth Industrial Revolution*. World Economic Forum.

Southerton, C. 2022. "Datafication." In *Encyclopedia of Big Data*, edited by J. Thompson, 358–361. Springer. https://doi.org/10.1007/978-3-319-32010-6_332.

Sparascio, C., S. Dal Lago, A. Manfredi, and A. Gabbiadini. 2023. "Working Objectification 2.0: A Theoretical Analysis of Datafication's Impact on Labor in the Next Future." *TPM: Testing, Psychometrics, Methodology in Applied Psychology* 30, no. 2: 215–229.

Stajkovic, A. D., and F. Luthans. 1998. "Self-Efficacy and Work-Related Performance: A Meta-Analysis." *Psychological Bulletin* 124, no. 2: 240–261. https://doi.org/10.1037/0033-2909.124.2.240.

Stephan, W. G., O. Ybarra, and G. Bachman. 1999. "Prejudice Toward Immigrants." *Journal of Applied Social Psychology* 29, no. 11: 2221–2237. https://doi.org/10.1111/j.1559-1816.1999.tb00107.x.

Stillman, T. F., R. F. Baumeister, and A. R. Mele. 2010. "Free Will in Everyday Life: Autobiographical Accounts of Free and Unfree Actions." *Philosophical Psychology* 23, no. 3: 435–454. https://doi.org/10.1080/09515089.2011.556607.

Yigitcanlar, T., K. Degirmenci, and T. Inkinen. 2024. "Drivers Behind the Public Perception of Artificial Intelligence: Insights From Major Australian Cities." *AI & Society* 39, no. 3: 833–853. https://doi.org/10.1007/s00146-022-01566-0.

Yogeeswaran, K., J. Złotowski, M. Livingstone, C. Bartneck, H. Sumioka, and H. Ishiguro. 2016. "The Interactive Effects of Robot Anthropomorphism and Robot Ability on Perceived Threat and Support for Robotics Research." *Journal of Human-Robot Interaction* 5, no. 2: 29–47. https://doi.org/10.5898/JHRI.5.2.Yogeeswaran.

Yzerbyt, V., D. Muller, C. Batailler, and C. M. Judd. 2018. "New Recommendations for Testing Indirect Effects in Mediational Models: The Need to Report and Test Component Paths." *Journal of Personality and Social Psychology* 115, no. 6: 929–943. https://doi.org/10.1037/pspa0000132.

Złotowski, J., K. Yogeeswaran, and C. Bartneck. 2017. "Can We Control It? Autonomous Robots Threaten Human Identity, Uniqueness, Safety, and Resources." *International Journal of Human-Computer Studies* 100: 48–54. https://doi.org/10.1016/j.ijhcs.2016.12.008.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.