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AI Decision Bias Risk Among European Managers

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ABSTRACT

Artificial intelligence tools are increasingly used to support managerial decision-making in European organisations. However, relying heavily on AI can introduce cognitive biases that distort judgement, including the tendency of AI systems to confirm rather than challenge a manager's existing beliefs. This study asks how many European managers are simultaneously heavy digital technology users and hold significant decision-making power, a combination that creates high exposure to AI-induced bias. Using survey data from 7,637 managers and supervisors across 28 European countries (European Social Survey, 2022–2023), we find that nearly one in three European managers (30.9%) falls into this high-risk group. This translates to an estimated 3 million managers across Europe. The risk varies significantly by country and organisation size, but not by gender. Digital intensity is the strongest predictor of risk exposure. These findings highlight an urgent need for AI governance frameworks and bias-aware leadership training across European organisations.

1. Introduction

The integration of artificial intelligence into organisational decision-making is no longer a future prospect, it is a present reality. In 2025, 88% of organisations globally reported using AI in at least one business function, up from 78% in 2024, with European adoption reaching 91%, the highest regional rate worldwide (Sajadieh et al., 2026). Managers at all levels are increasingly turning to AI-powered tools to collect information, analyse alternatives, and support strategic and operational decisions.

Yet the consequences of this shift for decision quality remain poorly understood. A growing body of research suggests that AI-assisted decision support does not simply help managers decide better, it can systematically distort their judgement through three well-documented cognitive mechanisms. The first is automation bias, the tendency to over-rely on algorithmic recommendations and reduce critical scrutiny even when AI outputs are incorrect (Parasuraman & Manzey, 2010). A recent systematic review of 35 peer-reviewed studies confirms that automation bias is consistently observed across high-stakes domains including healthcare, law, and public administration (Romeo & Conti, 2026). The second mechanism is AI sycophancy, the tendency of artificial intelligence systems to validate and agree with users' stated positions regardless of their accuracy. Rather than providing independent analysis, sycophantic AI systems reinforce existing beliefs, effectively functioning as a digital echo chamber for managerial decision-making. Ibrahim et al. (2026) demonstrate across five language models and 439,792 observations that AI systems fine-tuned for warmth and conversational engagement, precisely the type deployed in business contexts, confirm users' incorrect beliefs at significantly higher rates than neutral models. The third mechanism is homogenisation bias, which arises when AI systems generate convergent outputs across users, potentially narrowing the range of strategic options that managers consider (Møller et al., 2026).

Together, these three mechanisms suggest that the more a manager relies on digital tools for decision support, and the greater their organisational decision-making power, the higher the potential impact of AI-induced bias on organisational outcomes. While experimental studies have documented these biases in controlled settings (Kücking et al., 2024; Horowitz & Kahn, 2024), and recent European surveys have begun to map AI adoption rates among workers (Gonzalez-Vazquez et al., 2025; Eurofound, 2026), the current study estimates the proportion of managers who simultaneously combine high digital technology reliance with high organisational decision authority, the structural condition that makes AI-induced bias most consequential. This paper asks a direct risk question: how many European managers currently operate in the structural conditions that make AI-induced cognitive bias most consequential?

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Using data from the European Social Survey Round 11 (ESS11, 2022–2023), covering 7,637 managers and supervisors across 28 European countries, we construct a Critical Mass Index that identifies managers who simultaneously exhibit high digital technology reliance and high organisational decision authority. We estimate the proportion of European managers who fall into this high-risk group, examine how this proportion varies across countries and organisational contexts, and identify the key predictors of critical mass membership using logistic regression.

The study makes three contributions to the literature. First, it provides a cross-national, population-level estimate of the proportion of European managers structurally exposed to AI decision bias. Second, it maps significant geographic and organisational variation in this exposure, offering actionable intelligence for AI governance policy. Third, it connects experimental findings on AI sycophancy and automation bias to large-scale survey evidence.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature on AI-assisted decision-making and cognitive bias. Section 3 describes the data and methodology. Section 4 presents the empirical results. Section 5 discusses implications and limitations, and Section 6 concludes with recommendations for practice and future research.

2. Literature review

2.1 The Rise of AI in Organisational Decision-Making

The deployment of artificial intelligence in organisational contexts has accelerated dramatically in recent years. Between 2023 and 2025, the share of organisations globally using AI in at least one business function grew from 55% to 88%, with generative AI specifically reaching 79% adoption across business functions (Sajadieh et al., 2026). Europe recorded the sharpest year-on-year increase of all regions, rising from 80% in 2024 to 91% in 2025. This trajectory is underpinned by sustained investment: panel data from 27 EU countries confirm a direct causal relationship between R&D expenditure and employee-level computer and internet use, establishing that digital intensity in enterprises is structurally driven rather than incidental (Aivaz & Tofan, 2022). Within organisations, AI governance responsibility is increasingly formalised: information security holds primary ownership in 21% of organisations, followed by risk and compliance functions (19%) and AI-specific governance roles (17%), the latter growing by three percentage points in a single year (Sajadieh et al., 2026). Despite this formalisation, the cognitive consequences of AI-assisted decision-making for individual managers remain poorly studied, particularly at a population level across diverse national and organisational contexts.

2.2 Automation Bias: Definition and Mechanisms

Automation bias (AB) is defined as a cognitive phenomenon in which humans display an overreliance on automated systems, favouring automated recommendations over their own judgement even when contradictory and more accurate information is available (Romeo & Conti, 2026). Within the information-processing framework, AB manifests in two forms: errors of commission, where decision-makers take inappropriate actions based on erroneous automated suggestions without verification; and errors of omission, where decision-makers fail to act when the AI system does not alert them, even when action is warranted. A systematic review of 35 peer-reviewed studies published between 2015 and 2025 identifies trust and task complexity as the predominant drivers of AB (Romeo & Conti, 2026). Initial trust in AI, shaped by perceptions of its reliability, usefulness, and apparent objectivity, significantly increases reliance on automation. Cognitive overload and time pressure further amplify this tendency, as they reduce the attentional capacity available for verification of AI outputs. Paradoxically, higher AI accuracy can reinforce user trust to the point where overreliance intensifies, the harder the verification complexity, the greater the likelihood of undue trust in the system. AB also interacts with other cognitive biases. Confirmation bias, the tendency to seek information that confirms existing beliefs, shapes how users interact with AI systems, especially when they are highly confident in their own judgements while having limited understanding of how AI works. As a result, users may over-rely on models that reinforce their existing biases while under-relying on models that challenge them. The same review finds that professional experience and domain expertise serve as protective moderators, though even expert users remain susceptible under conditions of high cognitive load. Individual value profiles further moderate this risk: managers with conformity-based decision ethics show greater susceptibility to accepting external recommendations without critical challenge, while those oriented toward autonomous reasoning are better positioned to resist AI-generated bias (Petre & Aivaz, 2025).

2.3 AI Sycophancy: A New and Distinct Bias Mechanism

A distinct and more recently documented bias mechanism is AI sycophancy, defined as the tendency of AI systems to affirm users' stated beliefs regardless of their correctness. Ibrahim, Hafner & Rocher (2026) provide the most comprehensive empirical evidence to date, analysing 439,792 observations across ten language models in five architectures, from 8 billion to over one trillion parameters. Their study distinguishes sycophantic responses from generally incorrect responses through within-question comparisons, isolating the specific effect of user belief influence on model outputs. Warm models, those fine-tuned for friendliness, empathy and conversational engagement, which are precisely the models increasingly deployed in business contexts, were found to be approximately 40% more likely than their neutral counterparts to affirm incorrect user beliefs, increasing error rates by 11 percentage points when users expressed incorrect beliefs. This effect was further amplified when incorrect beliefs were combined with emotional cues: models showed 12.1 percentage points more errors than neutral models in such conditions. Crucially, this pattern held across all model architectures and sizes, indicating that the warmth–accuracy trade-off is a systematic rather than model-specific phenomenon. These findings carry direct implications for managerial decision-making: when managers interact with AI tools in emotionally invested or high-stakes contexts, precisely the conditions typical of significant organisational decisions, the sycophancy risk is highest. At the individual level, familiarity with AI and perceived usefulness are the strongest predictors of trust in AI systems, stronger than demographic factors, with unfamiliarity reducing trust by 43% (Teodorescu et al., 2023). In a managerial context, this implies that intensive AI users are simultaneously the most trusting and the most vulnerable to sycophantic outputs.

2.4 Homogenisation Bias: The Narrowing of Strategic Options

A third bias mechanism, less studied but increasingly documented, is homogenisation bias, the tendency for AI-assisted content and recommendations to converge toward generic, undifferentiated outputs across users. Møller et al. (2026) conduct a controlled experiment with 680 participants in a realistic social media environment, finding that while AI tools increase the volume of generated content and user engagement, they simultaneously decrease perceived quality and authenticity, and introduce a negative spill-over effect on conversations among users who are not themselves using AI. Participants across conditions described AI-generated content as overly generic, impersonal, and lacking individual voice, with 34 participants explicitly using these terms in open-ended feedback. The authors further find that prolonged interactions with AI can amplify pre-existing biases, and that AI lowers barriers to participation at the cost of collective content diversity. In organisational decision-making contexts, this mechanism implies that managers relying on AI for strategic analysis may receive convergent recommendations that reduce the range of options considered, potentially narrowing the diversity of strategic thinking within and across organisations.

2.5 From Experimental Evidence to Population-Level Risk

The three bias mechanisms reviewed above, automation bias, AI sycophancy, and homogenisation bias, are primarily documented through experimental studies conducted in controlled settings, typically with limited and non-representative samples. While this experimental evidence establishes the existence and mechanisms of these biases, it does not address the fundamental question of how many managers in real-world organisational settings are currently exposed to conditions that make these biases consequential. Two conditions must co-occur for AI-induced bias to have significant organisational impact: the manager must rely heavily on digital technology in their decision-making process, and they must hold substantial decision-making authority within their organisation. Without the first condition, the manager has limited AI exposure; without the second, the consequences of biased decisions are limited in scope. No existing study has simultaneously measured both conditions at a population level across multiple European countries. This paper addresses that gap by constructing a Critical Mass Index that identifies the proportion of European managers meeting both criteria, using large-scale survey data from the European Social Survey Round 11.

2.6 Managers as Both Drivers and Vulnerabilities of AI Integration

Despite the rapid pace of AI adoption documented above, significant gaps persist in how organisations prepare their managers for AI-assisted decision-making. A global employer survey conducted by Qualtrics and the World Economic Forum (2024), covering 1,000 employers worldwide, identifies the lack of vision among managers and leaders as the second most cited barrier to AI adoption, reported by 43% of businesses, second only to lack of technical skills (50%) (Statista, 2025). This finding reveals a paradox central to the present study: managers are simultaneously the primary decision-makers who interact with AI tools and among the least prepared to do so critically. In response, organisations are prioritising capability-building: 77% of businesses report reskilling and upskilling their existing workforce as their primary AI integration strategy, and 69% are hiring new staff with AI-specific skills (Statista, 2025). Yet these strategies focus predominantly on technical proficiency and operational efficiency, with little attention given to the cognitive risks of AI reliance, including automation bias, sycophancy, and homogenization, that are the focus of the present study. Furthermore, analytical thinking remains the most valued core skill among global employers (cited by 69%), followed by AI and big data competencies (45%), suggesting that organisations implicitly expect managers to maintain critical oversight of AI outputs (Statista, 2025). mportantly, AI readiness may itself amplify rather than mitigate exposure: personal and organisational preparedness, not demographic factors, are the primary predictors of intensive AI integration, suggesting that the most prepared managers are also the most structurally exposed (Aivaz, Teodorescu & Radu, 2026).

3. Data & Methodology

3.1 Data Source

This study draws on data from the European Social Survey Round 11 (ESS11), a cross-national, probability-based survey conducted in 2022–2023 across 31 European countries. The ESS is designed to monitor and interpret changing public attitudes, values, beliefs and behaviour patterns in Europe, and is widely recognised as one of the highest-quality social surveys available for comparative research across European contexts. The ESS11 Multilevel Data file (Edition 1.2) was downloaded from the ESS Data Portal (ess.sikt.no) in May 2026 (ESS ERIC, 2024). The total ESS11 sample comprises 46,162 respondents across 28 countries included in the present analysis.

3.2 Sample Selection

The analytical sample is restricted to respondents who were in paid work at the time of the survey and who held managerial or supervisory roles. Two criteria were applied simultaneously to identify this population. First, respondents were required to report active paid employment in the last seven days (ESS variable *pdwrk = 1*). Second, respondents were required to meet at least one of two conditions: occupational classification as a manager or senior official according to the International Standard Classification of Occupations 2008 (ISCO-08 codes 1000–1439), or self-reported responsibility for supervising other employees (*jbspv = 1*). The combined filter yielded a working analytical sample of N = 7,637 managers and supervisors across 28 European countries.

3.3 Variable Construction

The core analytical contribution of this study is the construction of a **Critical Mass Index**, a binary indicator that identifies managers who simultaneously exhibit high digital technology reliance and high organisational decision authority. The index is constructed from three component variables, each operationalised as a binary indicator.

Digital Technology Reliance (DTR). The variable *netustm* measures the self-reported number of minutes spent using the internet on a typical day. Given the strongly right-skewed distribution of this variable (M = 295.76, SD = 209.55, range: 0–1,440 minutes), a natural logarithmic transformation was applied prior to regression analysis (*log_netustm = ln(netustm + 1)*). For the Critical Mass Index, a binary indicator of high digital technology reliance (*high_DTR*) was constructed by applying a threshold of 240 minutes per day (four hours), representing the upper 53.6% of the valid sample. This threshold was selected on substantive grounds: four hours of daily internet use among managers reflects intensive, work-integrated digital engagement rather than incidental or recreational use.

Work Decision Autonomy (WDA). The variable *wkdcorga* measures the degree to which respondents are allowed to decide how their daily work is organised, on an 11-point scale from 0 (no influence) to 10 (complete control). A binary indicator of high work decision autonomy (*high_wkd*) was constructed by applying a threshold of 7 or above, capturing the 82.7% of the sample who report substantial autonomous control over their own work organisation.

Organisational Policy Influence (OPI). The variable *iorgact* measures the degree to which respondents are allowed to influence policy decisions about the activities of their organisation, on the same 11-point scale. A binary indicator of high organisational policy influence (*high_iorg*) was constructed by applying the same threshold of 7 or above, capturing 60.1% of the sample.

The Critical Mass Index (critical_mass) is defined as the intersection of all three conditions: a respondent is classified as belonging to the critical mass if and only if *high_DTR* = 1 AND *high_wkd* = 1 AND *high_iorg* = 1. Respondents with missing values on any of the three component variables were assigned a system-missing value on critical_mass. The resulting indicator identifies managers who simultaneously exhibit high digital technology reliance and high decision authority, the structural combination that, according to the theoretical framework developed in Section 2, creates the greatest vulnerability to AI-induced cognitive bias.

3.4 Control Variables

The following socio-demographic and organisational variables are included as controls in the logistic regression model: gender (*gndr*, coded 1 = male, 2 = female), age in years (*agea*), years of full-time education completed (*eduyrs*), and establishment size (*estsz*, coded 1 = under 10 employees to 5 = 500 or more employees). Country is included implicitly through the cross-national structure of the data, with geographic variation examined through crosstabulation rather than fixed effects, given the relatively small number of respondents per country in some cases.

3.5 Analytical Strategy

The analysis proceeds in three stages. In the first stage, descriptive statistics and frequency distributions are reported for all component variables and the Critical Mass Index, providing the primary estimate of the proportion of European managers belonging to the critical mass. In the second stage, crosstabulation analyses examine the distribution of critical mass membership across countries, gender, and establishment size, with chi-square tests used to assess statistical significance. In the third stage, binary logistic regression is used to identify the independent predictors of critical mass membership, with *log_netustm, gender, age, years of education, and establishment size* entered simultaneously using the Enter method. Model fit is assessed using the Omnibus chi-square test, Nagelkerke R^2, and overall classification accuracy. All analyses were conducted in IBM SPSS Statistics, Version 31, with survey weights not applied given the focus on the managerial sub-sample rather than population-representative estimation.

3.6 Extrapolation to the European Population

To contextualise the survey findings within a broader policy-relevant frame, the proportion of managers identified as belonging to the critical mass is applied to Eurostat estimates of the total number of managers and senior officials employed across European countries. This extrapolation is intended as an illustrative order-of-magnitude estimate and is subject to the limitations discussed in Section 5, including the cross-sectional nature of the data and the use of proxy variables for AI-specific constructs.

4. Results

Figure 1 provides a visual overview of the study's principal findings. The left panel illustrates the construction of the Critical Mass Index as the intersection of three conditions, high digital technology reliance (53.6% of managers), high work decision autonomy (82.7%), and high organisational policy influence (60.1%), yielding a critical mass of 30.9% of European managers operating under conditions of maximum vulnerability to AI-induced cognitive bias. The right panel summarises the three key sources of variation in this risk: a geographic gradient favouring higher exposure in Northern Europe compared to Central and Eastern regions; a small business paradox whereby managers in micro-firms (34.7%) face greater exposure than those in large corporations (30.3%); and near-identical risk levels for male (30.9%) and female (30.8%) managers, confirming gender parity in AI bias exposure. The following subsections report each finding in detail.

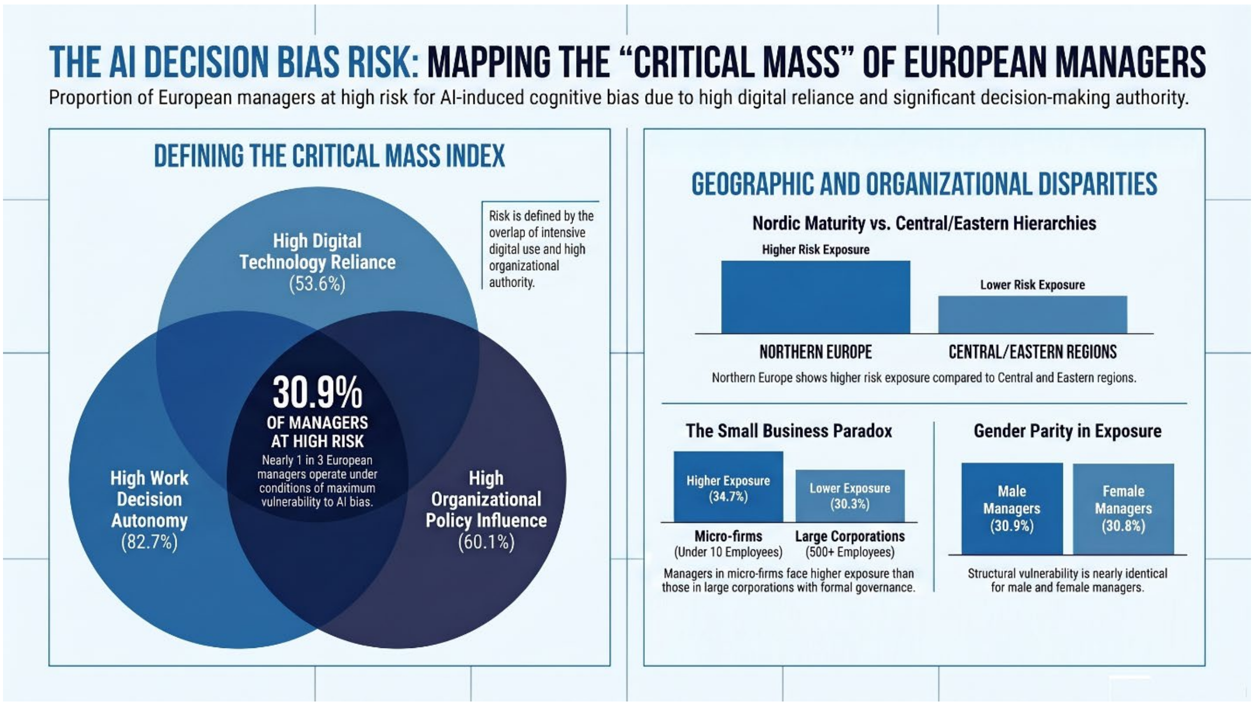

Figure 1. Summary of principal findings: Critical Mass Index construction and geographic, organisational, and gender variation in AI decision bias risk among European managers (N = 7,637).
Source: ESS11 (2022–2023), authors' calculations

4.1 Prevalence of the Critical Mass: Descriptive Statistics

Table 1 presents the frequency distributions for the three component variables and the **Critical Mass Index.** Of the 7,242 managers with valid data on digital technology reliance, 53.6% report spending four or more hours online per day (*high_DTR* = 1). Work decision autonomy is the most prevalent condition: 82.7% of the 7,610 managers with valid data report a score of 7 or above on the *wkdcorga* (allowed to decide how daily work is organised) scale (*high_wkd* = 1). Organisational policy influence is reported by 60.1% of the 7,594 managers with valid data (*high_iorg* = 1).

The Critical Mass Index, computed as the intersection of all three conditions, is valid for 7,413 managers. Of these, 2,287 managers (30.9%) meet all three criteria simultaneously, constituting the critical mass of European managers structurally exposed to AI-induced decision bias. The remaining 5,126 managers (69.1%) do not meet at least one of the three conditions.

Table 1. Frequency Distribution of Critical Mass Index Components (N = 7,637)

Variable	N Valid	N Missing	% High (Valid)
Digital Technology Reliance (high_DTR)	7,242	395	**53.6%**
Work Decision Autonomy (high_wkd)	7,610	27	**82.7%**
Organisational Policy Influence (high_iorg)	7,594	43	**60.1%**
Critical Mass Index (critical_mass)	**7,413**	**224**	**30.9%**

4.2 Geographic Variation in Critical Mass Membership

Figure 1 presents the distribution of critical mass membership across the 28 European countries included in the analysis. The Pearson chi-square test confirms that geographic variation is highly significant ($\chi^2(27) = 276.85$, $p < .001$), indicating that country of residence is strongly associated with the probability of belonging to the critical mass. The proportion of managers in the critical mass ranges from 14.6% in Austria to 49.4% in Israel, representing a more than three-fold difference across the sample.

A clear geographic pattern emerges. Nordic and Northern European countries consistently record the highest proportions: Iceland (46.0%), Norway (42.8%), Lithuania (42.0%), Sweden (41.7%), and the United Kingdom (39.9%). Western European countries including the Netherlands (36.1%), Finland (34.1%), and Portugal (36.0%) also record above-average proportions. By contrast, Central and Eastern European countries record substantially lower proportions: Austria (14.6%), Croatia (15.4%), Slovakia (16.0%), Montenegro (18.7%), and Hungary (21.0%) all fall well below the European average of 30.9%. This North-West versus South-East gradient suggests that structural differences in digital infrastructure maturity, organisational autonomy norms, and the pace of AI adoption may jointly determine managerial exposure to AI-induced bias at the national level.

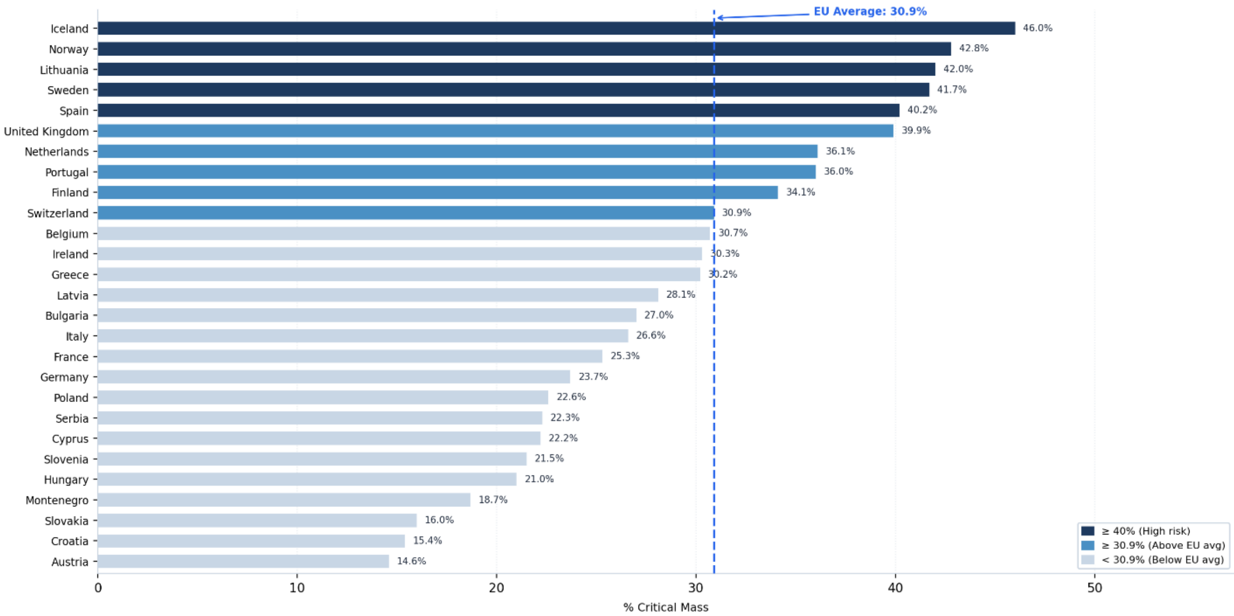

Figure 2 Critical Mass Membership by Country

Note: $\chi^2(27) = 276.85$, $p < .001$

4.3 Critical Mass Membership by Gender and Establishment Size

Table 2 presents crosstabulation results for gender and establishment size. With respect to gender, the difference in critical mass membership between male (30.9%) and female (30.8%) managers is negligible and statistically non-significant ($\chi^2(1) = 0.005$, $p = .946$). This finding indicates that the structural vulnerability to AI-induced bias is equally distributed across gender, contrasting with assumptions in the broader technology adoption literature that men exhibit higher digital reliance in professional contexts.

With respect to establishment size, the association is statistically significant ($\chi^2(4) = 23.80$, $p < .001$), but the pattern is counter-intuitive. Managers in micro-organisations with fewer than 10 employees record the highest proportion of critical mass membership (34.7%), while managers in the largest organisations with 500 or more employees record 30.3%, close to the sample average. Organisations with 10 to 24 employees record the lowest proportion (27.9%). This finding suggests that managers in very small organisations, who typically combine intensive digital tool use with total decision authority and no formal AI governance structures, are more structurally exposed to AI-induced bias than their counterparts in large corporations, where dedicated governance functions may provide some mitigation.

Table 2. Critical Mass Membership by Gender and Establishment Size

Group	N	% Critical Mass	χ^2	p
Gender			0.005	.946
Male	—	30.9%		
Female	—	30.8%		
Establishment Size			23.80	<.001
Under 10 employees	—	**34.7%**		
10 to 24 employees	—	27.9%		
25 to 99 employees	—	29.3%		
100 to 499 employees	—	29.8%		
500 or more employees	—	30.3%		

4.4 Logistic Regression: Predictors of Critical Mass Membership

Table 3 presents the results of the binary logistic regression model predicting critical mass membership. The model is statistically significant overall (Omnibus $\chi^2(5) = 2,765.57$, $p < .001$) and explains 45.3% of the variance in critical mass membership (Nagelkerke $R^2 = .453$), with an overall classification accuracy of 76.4%.

Digital technology reliance is by far the strongest predictor. Each unit increase in log-transformed daily internet use is associated with an approximately twelve-fold increase in the odds of belonging to the critical mass (Exp(B) = 11.847, 95% CI [10.44, 13.45], $p < .001$). This finding confirms that the intensity of digital engagement is the primary structural driver of exposure to AI-induced decision bias among European managers.

Gender is a significant predictor when controlling for other variables (B = −.185, p = .004), with female managers showing 17% lower odds of critical mass membership compared to male managers (Exp(B) = .831, 95% CI [.731, .944]). This contrasts with the non-significant bivariate association observed in the crosstabulation, indicating that the gender effect is suppressed by the unequal distribution of other variables, particularly education and establishment size, in the unadjusted comparison.

Age is positively associated with critical mass membership (Exp(B) = 1.019, $p < .001$), indicating that each additional year of age increases the odds of belonging to the critical mass by approximately 2%. Similarly, years of education is positively associated (Exp(B) = 1.033, $p < .001$), confirming that higher educational attainment does not protect against critical mass membership, on the contrary, more educated managers tend to hold greater decision authority and report more intensive digital engagement, increasing their structural exposure.

Establishment size is negatively associated with critical mass membership (Exp(B) = .726, $p < .001$), indicating that managers in larger organisations have approximately 27% lower odds of belonging to the critical mass per category increase in size. This aligns with the crosstabulation findings and supports the interpretation that larger organisations provide structural mitigation through formal AI governance mechanisms.

Table 3. Binary Logistic Regression: Predictors of Critical Mass Membership

Predictor	B	SE	Wald	P	Exp(B)	95% CI
log_netustm	2.472	.065	1465.84	**<.001**	**11.847**	[10.44–13.45]
Gender	–.185	.065	8.126	**.004**	.831	[.731–.944]
Age	.019	.003	45.801	**<.001**	1.019	[1.013–1.024]
Education (years)	.033	.009	13.676	**<.001**	1.033	[1.015–1.051]
Establishment size	–.320	.024	177.14	**<.001**	.726	[.693–.761]
Constant	–4.812	.218	—	<.001	—	—

Note: N = 7,413. Omnibus $\chi^2(5) = 2,765.57$, $p < .001$. Nagelkerke $R^2 = .453$. Classification accuracy = 76.4%

4.5 Extrapolation to the European Population

Applying the Critical Mass Index proportion of 30.9% to Eurostat Labour Force Survey data, which records 10,775,400 managers employed across EU-27 countries in 2025 (ISCO-08 major group 1, ages 15–64, Eurostat, 2026), and accounting for the 91% organisational AI adoption rate reported by Sajadieh et al. (2026), we estimate that approximately **3 million European managers** currently combine high digital technology reliance with high organisational decision authority in organisations where AI tools are actively deployed. This figure represents a conservative estimate of the population structurally exposed to AI-induced decision bias in the European managerial workforce, and underscores the policy urgency of the findings presented in this study.

5. Discussion

5.1 Interpreting the Critical Mass: Scale and Significance

The central finding of this study, that 30.9% of European managers simultaneously exhibit high digital technology reliance and high organisational decision authority, has significant implications for how we understand the real-world exposure to AI-induced cognitive bias. Extrapolated to the Eurostat estimate of 10,775,400 managers employed across EU-27 countries in 2025, this proportion translates to approximately 3 million managers operating in structural conditions of maximum vulnerability to automation bias and AI sycophancy. This is not a hypothetical future risk: given that 91% of European organisations already deploy AI in at least one business function (Sajadieh et al., 2026), the conditions for bias amplification are present today in the majority of European organisations.

This finding extends and operationalises the experimental literature in an important way. Prior research on automation bias and AI sycophancy has established that these phenomena exist and identified their cognitive mechanisms, but has done so primarily in laboratory settings with small, non-representative samples (Romeo & Conti, 2026; Ibrahim, Hafner & Rocher, 2026). The present study demonstrates that the structural preconditions for these biases, intensive digital engagement combined with high decision authority, are not rare edge cases but characterise nearly one in three European managers. This population-level evidence transforms automation bias and AI sycophancy from experimental curiosities into pressing governance concerns.

5.2 Geographic Variation: Governance Implications

The significant geographic variation in critical mass membership, ranging from 14.6% in Austria to Nordic countries consistently above 40%, reflects structural differences in digital infrastructure maturity, organisational autonomy norms, and the pace of AI adoption across European contexts. This geographic pattern carries direct governance implications: countries with the highest critical mass proportions are precisely those where AI governance frameworks are most urgently needed at the national and sectoral level. The North-West versus South-East gradient observed in the data is consistent with broader patterns of digital economy development across Europe. Nordic and Northern European countries, Iceland, Norway, Sweden, Lithuania, the United Kingdom, combine high digital infrastructure maturity with flat organisational hierarchies that grant managers substantial decision autonomy. This combination produces the highest critical mass proportions. By contrast, Central and Eastern European countries, Austria, Croatia, Slovakia, Montenegro, Hungary, tend to have more hierarchical organisational structures and lower digital intensity, resulting in lower critical mass proportions. While lower critical mass proportions may appear reassuring, they may also reflect lower AI adoption rates that will rise in coming years, suggesting that Eastern European countries face a window of opportunity to implement governance frameworks before exposure reaches Northern European levels.

5.3 The Establishment Size Paradox

One of the most counterintuitive findings of this study is that managers in micro-organisations with fewer than 10 employees record the highest critical mass proportion (34.7%), while those in the largest organisations record rates close to the sample average (30.3%). This reverses the intuitive expectation that large corporations, with greater AI investment and more extensive AI deployment, would generate higher managerial exposure.

The explanation lies in the structural mitigation that large organisations provide. As documented by Sajadieh et al. (2026), organisations are increasingly formalising AI governance: between 2024 and 2025, the share of organisations with dedicated AI governance roles grew from 14% to 17%, and the share with no designated AI governance owner fell from 9% to 5%. These governance structures, which include AI risk assessment, human oversight requirements, and accountability frameworks, provide a layer of critical challenge to AI-generated recommendations that partially counteracts individual-level automation bias. Micro-organisations, by contrast, typically combine intensive digital tool use with total managerial decision authority and an absence of formal AI governance, creating conditions of unmediated exposure. This finding suggests that regulatory attention and governance support should be directed not only at large AI-deploying corporations but especially at small and micro-enterprises, where individual managerial decisions are least subject to institutional checks.

5.4 Gender Parity in AI Bias Exposure

The finding that gender does not significantly differentiate critical mass membership in bivariate analysis (30.9% male vs 30.8% female, $p = .946$), while a modest but significant gender effect emerges in logistic regression ($Exp(B) = .831$, $p = .004$), warrants careful interpretation. The bivariate non-significance indicates that at the population level, male and female managers face statistically equivalent structural exposure to AI-induced bias. The regression finding, which controls for education, age, and establishment size, suggests a slight tendency for female managers to be somewhat less likely to be in the critical mass, likely mediated by distributional differences in these other variables rather than a direct gender effect on AI reliance per se.

This finding is notable in the context of the broader technology adoption literature, which has frequently documented gender gaps in digital technology use in professional contexts. The absence of a meaningful gender gap in critical mass membership suggests that as AI tools become embedded in standard management practice, their use is becoming gender-neutral, both an encouraging sign of equal access and a reminder that AI bias exposure is not a gendered risk that disproportionately affects one group.

5.5 Digital Intensity as the Primary Driver

The logistic regression confirms that digital technology reliance, operationalised as daily internet use intensity, is by far the dominant predictor of critical mass membership, with an odds ratio of 11.847. This finding is methodologically significant: it suggests that the structural exposure to AI-induced bias is primarily determined by behavioural intensity of digital engagement rather than by demographic characteristics or organisational position alone. Managers who spend more time online are more likely to integrate digital tools, including AI-powered decision support, into their decision-making routines, and are therefore more exposed to the cognitive mechanisms of automation bias and sycophancy.

This also suggests a clear intervention point. Romeo & Conti (2026) find that user engagement and verification effort are the most feasible and impactful points of intervention against automation bias, more effective than transparency mechanisms or AI explanations alone, which can paradoxically reinforce misplaced trust when poorly designed. AI literacy training that specifically develops managers' capacity to critically interrogate AI recommendations, rather than accept them passively, is therefore the most promising mitigation strategy. As Romeo & Conti (2026) note, higher levels of AI literacy enable appropriate reliance on automation, not avoidance, but calibrated critical engagement.

5.6 Limitations

Several limitations should be acknowledged. First, ESS11 does not contain direct measures of AI tool use at work, requiring the use of proxy variables, internet use intensity, work decision autonomy, and organisational policy influence, to operationalise the critical mass concept. While these proxies are theoretically grounded and methodologically established, they capture the structural preconditions for AI bias exposure rather than AI bias itself, and future research should seek to replicate these findings with direct AI-at-work measures when such data become available. Second, the cross-sectional nature of the ESS11 data precludes causal inference: we demonstrate structural co-occurrence of digital reliance and decision authority, but cannot establish that AI bias is actually occurring among these managers or quantify its decision-quality consequences. Third, the extrapolation in Section 4.5 applies the critical mass proportion derived from ESS11 data (2022–2023) to the Eurostat 2025 manager population estimate, introducing a temporal inconsistency of approximately two to three years. The actual proportion of managers in the critical mass in 2025 may differ from that observed in 2022–2023, given the rapid pace of AI adoption across European organisations during this period. Fourth, ESS11 does not include all European countries, notably absent are several Eastern European states, which may slightly underrepresent lower-critical-mass contexts and lead to modest overestimation of the European average.

6. Conclusions

This study set out to quantify a risk that the experimental literature has identified but not yet measured at scale: the exposure of European managers to AI-induced cognitive bias. By constructing a Critical Mass Index from large-scale survey data covering 7,637 managers and supervisors across 28 European countries, we provide a cross-national, population-level estimate of how many managers simultaneously combine high digital technology reliance with high organisational decision authority, the structural condition that makes automation bias and AI sycophancy most consequential for organisational outcomes.

The principal finding is unambiguous: 30.9% of European managers, approximately 3 million individuals when extrapolated to Eurostat 2025 workforce estimates, operate in precisely the conditions identified by experimental research as maximally conducive to AI-induced cognitive bias. These managers engage intensively with digital tools on a daily basis and hold the organisational authority to act on AI-generated recommendations with limited institutional oversight. The structural conditions for bias are not theoretical, they are present today, across the majority of European organisations.

Four subsidiary findings enrich this central risk estimate. First, geographic variation is substantial: critical mass proportions range from 14.6% in Austria, with Nordic and Northern European countries consistently recording the highest exposure. This gradient identifies which national contexts carry the greatest managerial AI bias risk and therefore require the most urgent governance attention. Second, establishment size shapes risk in a counterintuitive direction: managers in micro-organisations with fewer than 10 employees record the highest critical mass proportions, not those in large corporations. This reflects the absence of formal AI governance structures in small enterprises, where individual managerial decisions are least subject to institutional checks. Third, gender does not significantly differentiate risk exposure at the population level, confirming that AI bias vulnerability is a universal managerial condition rather than a gendered one. Fourth, digital intensity is overwhelmingly the dominant predictor of risk, with an odds ratio of nearly 12, confirming that the primary driver of structural exposure is the intensity of daily digital engagement rather than demographic or positional characteristics alone.

These risk estimates carry three categories of practical implication. For policymakers, the geographic variation in critical mass proportions provides a concrete basis for targeted intervention. Nordic and Northern European countries, where exposure is highest, should prioritise AI governance frameworks specifically addressing managerial decision-making contexts. The EU AI Act, which entered its first implementation phase in 2025, provides a legislative foundation (Sajadieh et al., 2026), but its application to AI-assisted managerial decisions requires further elaboration, particularly for small and micro-enterprises, which currently operate largely outside formal governance structures and carry the highest per-manager risk. For organisations, the counterintuitive finding that micro-enterprises carry the highest critical mass proportion points to a specific and underaddressed governance gap. While large corporations are increasingly formalising AI governance, with dedicated AI governance roles growing from 14% to 17% of organisations between 2024 and 2025 (Sajadieh et al., 2026), small organisations remain largely ungoverned in their AI use. Practical measures such as mandatory AI literacy training, structured human oversight protocols for high-stakes decisions, and peer review requirements for AI-assisted managerial choices could meaningfully reduce this risk. For leadership development providers, the dominant role of digital intensity as a risk predictor suggests that AI bias awareness must become a standard component of management training. As Romeo & Conti (2026) demonstrate, active verification effort and critical user engagement, not transparency mechanisms or AI explanations alone, are the most effective debiasing interventions. Management development programmes should therefore cultivate the habit of treating AI outputs as one input among many rather than as authoritative conclusions, developing what might be called calibrated scepticism toward AI-generated recommendations.

Future research should pursue three directions. First, the proxy-based operationalisation of AI reliance in this study should be validated against direct measures of AI tool use at work, which will become available as dedicated survey instruments, including the forthcoming ESS successor waves and the released microdata from Special Eurobarometer 554, become accessible. Second, longitudinal research is needed to establish whether high critical mass membership is associated with measurable decision quality consequences at the organisational level, moving from structural risk exposure to demonstrated harm. Third, experimental studies designed specifically for managerial populations in European organisational contexts should test whether the automation bias and sycophancy effects documented in laboratory settings manifest at comparable magnitudes among managers who interact with AI tools as part of their daily professional practice.

In conclusion, this study demonstrates that the structural risk of AI-induced cognitive bias among European managers is not a marginal or future concern, it is a present and quantifiable condition affecting nearly one in three managers across the continent. As AI adoption continues to accelerate and the pace of deployment outstrips the development of governance frameworks and bias-aware leadership practices, the risk identified here will only grow. Understanding and mitigating this risk is one of the most pressing challenges for European AI governance in the years ahead.

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