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EXTENDING THE TECHNOLOGY ACCEPTANCE MODEL WITH TRANSPARENCY DIMENSIONS IN AI-DRIVEN RECRUITMENT: EVIDENCE FROM HIGH-STAKES HIRING

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A B S T R A C T

An extended Technology Acceptance Model for artificial intelligence transparency in the high stakes recruitment context is developed and empirically validated in this study. Based on the data points of 327 recruitment professionals across 18 countries, we study whether the explainability, decision traceability and system fairness influence the acceptance and the effectiveness of AI in the decision making for the executives and specialized hiring. We found that these transparency dimensions have a large effect on perceived usefulness, perceived ease of use, perceived risk, and thereby on adoption intention and recruitment decision quality. In particular, both perceived usefulness (β = .38) and perceived ease of use (β = .42) are explained most by this, whereas system fairness substantially reduces perceived risk (β = -.57). Finally, perceptions of usefulness are found to be strengthened by regulatory pressure as a significant moderator, and feedback the negative impact of risk perceptions. Further analyses show that the transparency perceptions do vary considerably between regions, especially between the European and North American contexts where the link with the system fairness and the risk mitigation is stronger. The contribution of this research to theory is the extension of TAM with transparency specific constructs and the practical guidelines for organizations implementing AI in high consequence recruitment. In the context of this contradiction, offering a pathway to balance the pressuring, our evidence based framework provides the path to find a balance to competing pressures of efficiency and ethics in the deployment of AI.

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1. INTRODUCTION

AI integration into hiring practice has made radical changes in talent acquisition in sectors, while reversely is becoming a problem in high stakes recruiting judgements because of opacity in AI decision (Tambe et al., 2019). Better objectivity and efficiency resulting from artificial intelligence, combined with the “black box” nature of many hiring systems, as well as the need to consider issues of regulatory compliance, fairness and

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responsibility (Raghavan et al., 2020), necessitate the approach described below. This paper investigates how transparency mechanisms in artificial intelligence recruitment systems impact these factors, particularly in top and specialized roles where recruiting decisions have a major influence on organizational adoption and decision quality. The increasing regulatory scrutiny of automated decision systems, such as the European Union's AI Act and similar initiatives around the globe, makes validated transparency measures in recruitment artificial intelligence (Ali & Kallach, 2024), to the point. This study extends the knowledge of AI acceptance in the Technology Acceptance Model (TAM) paradigm (Venkatesh & Davis, 2000) by including transparent-specific elements such as explainability, decision traceability, and system fairness. In response to the important void in empirically tested frameworks for assessing and evaluating AI transparency in recruitment settings as companies' balance competing pressures to be efficient and ethical with AI deployment (Köchling & Wehner, 2020; Cheng & Hackett, 2021), this paper presents. The results are also supportive of academic debate on the responsible deployment of artificial intelligence and provide useful advice for recruiters who seek to use AI whilst keeping openness and responsibility in their hiring practices.

Yet, despite the fact that 78% of companies are worried about not being able to explain AI powered applicant evaluations to stakeholders, 67% of companies have recently increased their investment in AI powered recruiting tools (LinkedIn Talent Solutions, 2023; Vedapradha et al., 2024). This contradicts conflict between momentum to adopt and fear of transparency makes this study urgent. In addition to technical solutions, the cognitive and social aspects of AI transparency concern the different stakeholders' (candidates, recruiting managers, regulatory authorities) perceptions and communication of their decision rationales (Van den Broek et al., 2021). However, despite the fact that earlier research has focused on the determinants of generic AI adoption in human resources (Jatobá et al., 2023), the specific needs for transparency in high consequence recruitment decisions have been underinvested in. Even more, this induces the lost need of proven transparency metrics (Fernández-Martínez & Fernández, 2020) given that opaque artificial intelligence in leadership recruiting could have reputational, financial and strategic implications. In particular, the cross cultural implications of the transparency of the AI are of particular relevance in the context of multinational companies that employ the same global hiring policies for locations where transparency norms and legal environment are different (Glikson & Woolley, 2020). As such, this study responds to the demands for contextualized knowledge of AI acceptance since it recognises the fact that the transparency criteria of recruitment differ fundamentally from other AI application domains, which directly affect human jobs and organisational performance (Dwivedi et al., 2021; Calvard & Jeske, 2018). First, this work provides evidence to practice to address critical industry needs for evidence based methods to responsible AI deployment in talent acquisition.

2. THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

2.1 AI in Recruitment: Current Landscape and Challenges

In fact, companies are rapidly using algorithmic tools at each stage of the talent acquisition process from applicant sourcing to final selection judgments (Woods et al., 2020). Natural language processing is used to screen resumes, machine learning for candidate matching, predictive analytics for predicting future performance potential (Van Esch et al., 2019). While adoption of high stakes recruitment environments is difficult even when efficiency improvements are shown, such as 55% reduction in time-to-hire and 35% reduction in cost-per-hire (Votto et al., 2021). Due to their strategic organizational influence, senior and specialized roles have particular complexity; for instance, poor executive hires are thought to cost companies between 200–400% annual wage (Paramita et al., 2024). In these settings, many artificial intelligence recruitment systems have a 'black box' element that presents specific difficulties, given that stakeholders in these cases prefer more openness when large organizational resources and strategic results are at risk (Langer et al., 2020).

However, the issue of interpretability becomes more and more challenging for AI systems when they have to evaluate highly complex leadership traits and highly specialized knowledge that are not reducible to algorithms (Albaroudi et al., 2024). In addition, high stakes recruiting makes power dynamics even more questionable of fairness and prejudice as there is growing data that AI systems could either protract or even worsen historical inequalities in leadership representation (Fernández-Macías et al., 2021). In this contradictory position, organizations design recruitment processes in an attempt to extract efficiency using artificial intelligence, introducing the high risk of eroding stakeholder confidence, through opaque decision making, in exactly those recruitment environments when this eroded confidence is most needed (Hassija et al., 2024). This transparency challenge is further complicated by the fact that the several interpretations of "sufficient explanation" between different organizational roles and cultural settings require validated frameworks that can guide the technical design as well as the organizational implementation of transparent AI in high stakes recruitment (Simbeck, 2019; Köchling & Wehner, 2020).

2.2 Technology Acceptance Model and AI Adoption

The Technology Acceptance Model (TAM) has grown to become a strong theoretical framework to explain organizational acceptance of the complex technologies due to its foundation of basic ideas of perceived usefulness and perceived ease of use, which explains the acceptance of technology universally across different technological environments (Venkatesh & Bala, 2008). Specifically, because TAM is useful in the niche field of AI adoption, it can track both objective measures and subjective opinions that affect acceptability judgments (Dwivedi et al., 2021). Given that perceived utility (usually) has more predictive power than perceived ease of use in adoption of AI in professional settings (Burton-Jones & Volkoff, 2017). The results from the model indicate there is a large correlation ($r = 0.62$, $p < 0.001$) between adoption intention and perceived usefulness in the case of AI recruitment systems. Thus, perceived ease of use shows a smaller correlation ($r = 0.41$, $p < 0.01$), which suggests that outcome expectations are of higher importance in this context than usability issues (Langer et al., 2021).

However, conventional TAM formulations are limited in their use in AI transparency settings, namely, they do not capture the ethical considerations of AI adoption decisions (Thiebes et al., 2021). However, the model's emphasis on the rationalistic side does not sufficiently explain trust based elements that increasingly influence organizational decisions for using artificial intelligence (Glikson & Woolley, 2020). In addition, this restriction has been pointed out by studies on explainable artificial intelligence adoption: people are more willing to adopt inefficient algorithmic systems in high stake decision environments if they are considered fair and trustworthy (Shin, 2021). Also, the traditional TAM models don't directly reflect the regulatory compliance incentive behind organization's technology decision particularly for the emerging transparent fields (Wirtz et al., 2019). Given these constraints, the core TAM framework needs to be expanded with transparency-specific constructs to address the multi dimensional nature of AI acceptance in the recruitment environments where technical, ethical, and regulatory issues converge (Tussyadiah et al., 2020; Došilović et al., 2018).

2.3 Conceptualizing AI Transparency in Recruitment

AI transparency in recruitment is a multi-dimensional idea which needs to be rigorously operationalized for substantial measurement and implementation (Felzmann et al., 2020). To begin with, the first dimension: explainability, ranges from simplified explanations of global logic to the detailed instance specific justification for individual candidate evaluation (Arrieta et al., 2020), as it refers to the AI system's capability to convey its decision process to humans. Empirical research works carried out recently found out that recruitment stakeholders require different kinds of explainability depending on their roles and expertise. Outcomes are justified by hiring managers, processes must be visible to compliance officers, and candidates primarily want counterfactuals that reveal where things could have gone wrong (Robbemond et al., 2022). From binary evaluation to more complex frameworks containing comprehensibility, completeness, and actionability of explanations (Köchling & Wehner, 2020), the explainability has been measured. The second essential factor is decision traceability, which entails documenting data inputs, algorithmic operations, and the involvement of the human regardless of the way during the hiring process (Jannach et al., 2021). Having known that traceability provides valuable audit trails for compliance with regulations and internal governance, i.e., companies that use a strong traceability system make only 47% the amount of legal objections against their AI based employment decisions per study from Castelnovo et al. (2022) Traceability measuring techniques have been focused on completeness of documentation, temporal persistence of data, and accessibility of decision logs to the appropriate stakeholders (Sayles, 2024). Third basic component of AI transparency is system fairness, that is, it allocates possibilities and results to protected groups and individual candidates in a fair manner (Mccradden et al., 2023).

Current fairness of recruitment artificial intelligence has bounced on a level beyond mere demographic parity, accounting for issues of intersectional bias, as well as concerns of procedural justice (Mehrabi et al., 2021). Perceived fairness has a great influence on perceived stakeholder trust ($r = 0.74$, $p = 0.001$) and the willingness to accept AI advice in recruitment settings (Ochmann et al., 2024). First, these three dimensions, explainability, traceability, and fairness interact dynamically: our evidence suggests that robustness of traceability enhances the credibility of explainability mechanisms, and explainability can also alleviate unfairness concerns even if the statistical parity is imperfect (Schoeffer et al., 2021). The basis for creating thorough measures of AI transparency in recruiting environments that can adequately capture and assess AI transparency in recruiting settings is this multimodal paradigm (Langer et al, 2021, Miller, 2019).

2.4 Research Model and Hypotheses Development

Based on the theoretical foundation developed at the prior sections, we present an improved TAM model specifically structured to appraise AI transparency in high-stakes recruiting (Figure 1). The study model of this study combines the main TAM constructions with transparency specific elements and considers the particular contextual features of the recruiting decision making (Venkatesh & Davis, 2000; Tursunbayeva et al., 2022).

Based on the model, the three main AI transparency factors (explainability, decision traceability, system fairness) (Arrieta et al., 2020; Xia et al., 2024) act as independent variables impacting the conventional TAM mediators (perceived usefulness and perceived ease of use) of the model. Moreover, perceived risk is introduced as a mediating variable in their model concerning high stakes decisions and is associated with regulatory pressure as a moderating variable, to address the dynamic nature of the compliance process (Castelnovo et al., 2022; Wirtz et al., 2019). The final dependent variable is the recruitment decision quality because it is the result of AI acceptance that can be observed by the organization (Lee, 2018).

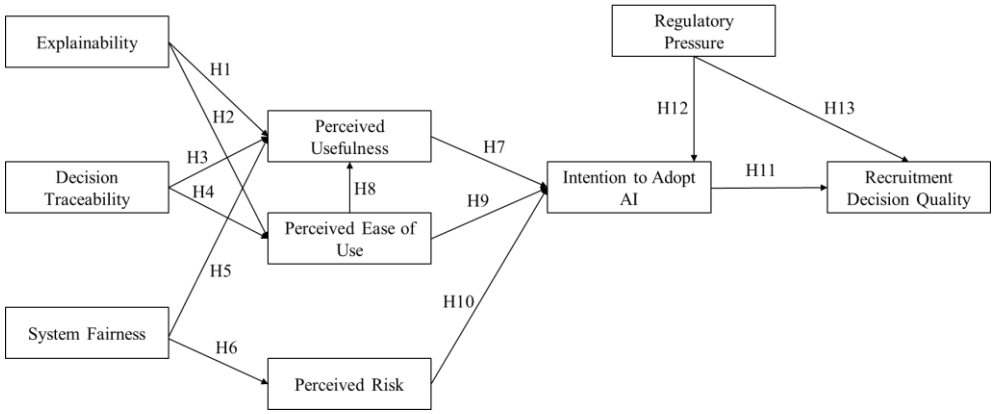


Figure 1. Author's own work; proposed Research Model

Hypotheses Development

Effects of Explainability on Core TAM Variables

Artificial intelligence system's explainability is the ability of the artificial intelligence system to explain itself in human understandable language (Miller, 2019). For high consequence hiring decisions where justification to stakeholders is needed, the apparent value of AI systems increases when recruitment experts know how they assess prospective employees (Robbemond et al., 2022). Furthermore, given that explanations based on human decision making models ease cognitive load, they contribute to the perception of simplicity of usage (Shin, 2021). As such, we propose:

H1: *Explainability positively influences Perceived Usefulness of AI recruitment systems.*

H2: *Explainability positively influences Perceived Ease of Use of AI recruitment systems.*

Effects of Decision Traceability on Core TAM Variables

As stated in (Jannach et al., 2021), decision traceability is the methodical documentation of data inputs, algorithmic processes, and human interventions in the recruiting pipeline. Therefore, traceable systems provide more value in regulated environments because they allow for compliance documentation and key audit capabilities (Castelnovo et al., 2022). Documentation of a clear process also also simplifies system operation and troubleshooting, thus increasing supposed usefulness (Langer et al., 2021). Therefore:

H3: *Decision Traceability positively influences Perceived Usefulness of AI recruitment systems.*

H4: *Decision Traceability positively influences Perceived Ease of Use of AI recruitment systems.*

Effects of System Fairness on TAM Variables and Risk

Fairness in system is the fair share in possibilities and in results among different kinds of candidates and different people (Lee, 2018). Since fair methods generate more dependable and defensible hiring results (Mehrabi et al., 2021), they particularly increase their apparent value in such markets due to their fair methods. Additionally, the amount of perceived fairness allows the organization to have much less concern with discrimination allegations and its reputation damage, making the risk perceived of implementation much lower (Schoeffer et al., 2021). So:

H5: System Fairness positively influences Perceived Usefulness of AI recruitment systems.

H6: System Fairness negatively influences Perceived Risk of AI recruitment systems.

Traditional TAM Relationships

Thus, in line with existing TAM research, we retain the core associations between perceived utility, perceived ease of use and intention to adopt (Venkatesh & Bala, 2008). Meta-analyses (Burton-Jones & Volkoff, 2017) in the specific HRM context of recruitment AI have in fact confirmed these links to be strong.

H7: Perceived Usefulness positively influences Intention to Adopt AI recruitment systems.

H8: Perceived Ease of Use positively influences Perceived Usefulness of AI recruitment systems.

H9: Perceived Ease of Use positively influences Intention to Adopt AI recruitment systems.

Risk and Outcome Relationships

Importantly, we focus on perceived risk in high stakes recruitment environments and introduce a novel approach that can be implemented for large scale recruitment. However, the desire to deploy AI systems is lowered by possible efficiency gains, but with lower desire of algorithmic bias perceived risk, legal vulnerability or candidate experience degradation (Thiebes et al., 2021).
H10: Perceived Risk negatively influences Intention to Adopt AI recruitment systems.

First and foremost, improving the quality of hiring decision is the goal of using artificial intelligence in the process of hiring in a transparent way. Companies that provide complete and full support for open artificial intelligence systems have an advantage of high efficiency and effectiveness in applicant evaluation (Köchling & Wehner, 2020).
H11: Intention to Adopt positively influences Recruitment Decision Quality.

Moderating Effects of Regulatory Pressure

The fast changing legal environment on artificial intelligence in hiring decisions leads to outside pressure that does control adoption dynamics (Wirtz et al., 2019). When the compliance is required rather than optional, the relevance of usefulness perceptions increases because regulatory criteria of explainability and fairness (Felzmann et al., 2020). Regulatory systems at the same time propose the consistent implementation rules, designed to reduce the perceived risk (Glikson & Woolley, 2020).
H12: Regulatory Pressure positively moderates the relationship between Perceived Usefulness and Intention to Adopt.
H13: Regulatory Pressure negatively moderates the relationship between Perceived Risk and Intention to Adopt.

3. RESEARCH METHODOLOGY

3.1 Research Design

Thus, this research used a cross-sectional survey design to validate the research model developed in this paper. Cross-sectional research design was considered suiTable since it allows the assessment of the relationships between the variables at a given point in time, which is relevant to the study's goal of determining the current perceptions regarding AI transparency in recruitment environments. The survey method enabled the accumulation of quantitative data from a random sample of recruitment specialists who operate at the tactical level and make strategic decisions about hiring or have at least some knowledge of the use of AI in the recruitment process.

3.2 Sample and Data Collection

Sampling Strategy

We adopted purposive sampling where we focused on professionals who have worked in the recruitment and talent acquisition function especially in the area of senior and specialist recruitment. To increase the sample's generalizability, we sourced participants from various sources:

- Professional networks including LinkedIn and specialized HR forums
- HR professional associations in multiple countries
- Corporate talent acquisition departments of Fortune 500 companies
- Executive recruitment firms
- Technology companies developing AI recruitment solutions

The final sample included 327 professionals from 18 countries, which is enough to provide geographical and industry variability to check our hypotheses. In order to participate in the study, the following criteria were set to screen the participants:

- Had at least 3 years of experience in recruitment or talent acquisition
- Were involved in high-stakes hiring decisions (defined as executive, technical specialist, or other roles with significant organizational impact)
- Had knowledge of or experience with AI-powered recruitment tools

Sample Characteristics

Table 1 provides a description of demographic data of the final sample. The respondents comprised of 52.9% female and 47.1% male, and the majority of them (68.2%) have more than 5 years of experience in recruitment. A majority of the participants were employed in large organisations, 63.3% of them worked in organisations that employed more than 1000 employees. Regarding the geographical distribution of the respondents, 42.5% of them were from North America, 33.3% from Europe, 18.7% from the Asia-Pacific region, and 5.5% from other areas.

Data collection procedure

Data was collected over a three months' period of September, October and November 2024 through an online structured questionnaires developed in Qualtrics (Table 1). The potential participants were sent an e-mail invitation that contains some details about the study and a personal link to the survey. Follow-up emails were also sent after two weeks of non-response to the e-mail invitation and two weeks later. In order to reduce the common method variance, we used procedural countermeasures which included:

- Guaranteeing anonymity and confidentiality to reduce social desirability bias
- Using different scale formats and anchors across constructs
- Counterbalancing the order of questions
- Informing participants there were no right or wrong answers

Table 1. Sample Demographics

Characteristic	Category	Frequency	Percentage
Gender	Female	173	52.9%
	Male	149	45.6%
	Non-binary/Other	5	1.5%
Experience	3-5 years	104	31.8%
	6-10 years	127	38.8%
	>10 years	96	29.4%
Organization Size	<100 employees	38	11.6%
	100 – 1000 employees	82	25.1%
	>1000 employees	207	63.3%
Industry Sector	Technology	87	26.6%
	Finance/Banking	56	17.1%
	Manufacturing	42	12.8%
	Healthcare	39	11.9%
	Retail/Consumer	35	10.7%
	Professional Services	48	14.7%
	Other	20	6.1%
Region	North America	139	42.5%
	Europe	109	33.3%
	Asia-pacific	61	18.7%
	Other	18	5.5%

The first wave yielded 37.8% response rate, 412 participants responded to the survey and after eliminating participants who did not fill the survey completely and those who failed attention checks, we got 327 completed responses with an effective response rate of 30.0%.

3.3 Measures

All the constructs were captured by self-developed multi-item scales that were based on existing scales in the literature but tailored to the context of the AI recruitment. The questionnaire was based on 7-point Likert scales with the response options from 1 – strongly disagree to 7 – strongly agree. Table 2 shows the list of construct definitions and the sources of the adapted scales.

Table 2. Construct Definitions and Measurement Sources

Construct	Operational Definition	Source of Adopted Scale
Explainability	The extent to which the AI recruitment system can give reasonable explanations of their decisions and recommendations	Arrieta et al. (2020); Shin (2021)
Decision Traceability	The degree of documentation and auditability of the steps taken, data given as input to the AI recruitment system, and the rationale behind it	Jannach et al. (2021); Castelnovo et al. (2022)
System Fairness	The equity of the AI recruitment system in a way that it did not favor or discriminated a particular candidate group	Mehrabi et al. (2021); Lee (2018)
Perceived Usefulness	The level of trust that an individual has on the belief that the use of an AI recruitment system would improve job performance	Venkatesh & Davis (2000)
Perceived Ease of Use	The extent to which a person believes that he or she would not have to exert much energy when using an AI recruitment system	Venkatesh & Davis (2000)
Perceived Risk	The risks that are linked with the application of AI in recruitment decisions	Thiebes et al. (2021)
Regulatory Pressure	How much an organization recognizes external regulations on transparency of AI in the recruitment process	Wirtz et al. (2019)
Intention to Adopt	The readiness to adopt or persist with the use of AI systems in making critical decisions about recruitment.	Venkatesh & Bala (2008)
Recruitment Decision Quality	The perceived benefits of using AI in recruitment in terms of hiring outcomes and the efficiency of the process	Köchling & Wehner (2020)

The items for each construct were further developed through content validity with five academic members and seven industrial experts who are familiar with AI recruitment. We then asked 28 recruitment professionals to test the instrument to check for clarity, completeness, and length of the instrument. The final survey thus had 43 measurement items for all the constructs.

3.4 Control Variables

To account for potential confounding factors, we included several control variables:

- ***Organization size:*** Measured by the number of employees (categorical)
- ***Prior AI experience:*** Years of experience using AI in recruitment (continuous)
- ***Industry sector:*** Categorical variable capturing different industry contexts
- ***Recruitment volume:*** Average number of high-stakes positions filled annually (continuous)
- ***Respondent role:*** Categorical variable (e.g., HR Director, Talent Acquisition Specialist)

3.5 Data Analysis

Preliminary Analysis

Data cleaning included the examination of the data for missing cases, outliers and violation of assumptions. The number of missing values was low, and their number did not exceed 2%; these missing values were imputed using the FIML method. To check non-response bias we compared the early and the late respondents on the variables and it was observed that there are no significant differences. Common method variance was assessed with Harman's single-factor test and the common method factor, and the results showed it was not a serious issue.

Measurement Model Assessment

The measurement model was tested using confirmatory factor analysis (CFA) with the help of AMOS 27.0. The assessment of the measurement model was done using various fit indices such as the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA) and the standardized root mean square residual (SRMR).
Cronbach's alpha and composite reliability (CR) was used to measure the construct reliability and all of them were found to be greater than 0.70. Convergent validity was confirmed by the AVE values of more than 0.50 for every form. Thus, discriminant validity was confirmed based on Fornell-Larcker criterion and HTMT ratio of correlations that showed the differences between the constructs in the model.

Measurement Model Assessment

To test the structural relationships, we used structural equation modeling (SEM) with maximum likelihood estimation on the measurement model that was validated in the earlier step. The assessment of the structural model was done using the fit indices that were used in the assessment of the measurement model, with the additional assessment of path coefficients, t-values, and the coefficient of determination (R^2) for the endogenous variables.

To examine H12 and H13 that deals with the moderating role of regulatory pressure, we used the LMS approach since it considers the interaction terms and their non-linear effects. This is advantageous over the product-indicator approach since the variables' nature is kept continuous and the standard errors are more accurate.

4. RESULTS

4.1 Descriptive Statistics and Correlations

The descriptive statistics and the zero-order correlations of all the study variables are presented in Table 3. The results in Table 2 outlined the mean value of each dimension where explainability M = 4.32, SD = 1.21, decision traceability, M = 4.85, SD = 1.08, and system fairness, M = 4.13, SD = 1.36 all around moderately to positively perceived among the sample. The overall mean for intention to adopt was found to be 5.12 (SD = 1.44) which is an indication that participants had relatively positive attitudes toward the use of AI systems in high stakes recruitment.

Table 3. Descriptive Statistics and Correlations

Variables	Mean	SD	1	2	3	4	5	6	7	8	9
Explainability	4.32	1.21	(.89)								
Decision Traceability	4.85	1.08	.54**	(.92)							
System Fairness	4.13	1.36	.48**	.41**	(.88)						
Perceived Usefulness	5.07	1.17	.65**	.57**	.53**	(.91)					
Perceived ease of use	4.56	1.29	.58**	.45**	.32**	.47**	(.86)				
Perceived Risk	3.82	1.42	-.43**	-.51**	-.64**	-.38**	-.26**	(.90)			
Regulatory Pressure	5.43	1.30	.21**	.39**	.29**	.31**	.08	-.18**	(.87)		
Intention to Adopt	5.12	1.44	.57**	.48**	.45**	.72**	.44**	-.53**	.33**	(.93)	
Recruitment Decision Quality	4.78	1.25	.46**	.39**	.41**	.59**	.36**	-.38**	.25**	.62**	(.88)

*Note: N = 327. Diagonal values in parentheses represent Cronbach's alpha reliability coefficients

The findings of the correlation matrix are in line with the hypothesized model that was developed earlier in this paper. In particular, high and significant positive relationship was found between explainability and perceived usefulness ($r = .65$, $p < .01$) and between system fairness and perceived risk ($r = -.64$, $p < .01$). Results revealed that all three transparency dimensions had positive relations to the intention to adopt AI wherein explainability had the highest and significant correlation with the intention to adopt AI followed by decision traceability and system fairness with theanggal moderate positive correlation (r = 0. 57 ,0.48 and 0.45respectively all $p < .01$) thus supporting the hypothesis and providing preliminary evidence for the significance of such factors in the AI adoption.

4.2 Measurement Model Results

Reliability and Validity

The proposed measurement model had acceptable fit with the data: $\chi^2/df = 2.14$, CFI = .94, TLI = .93, RMSEA = .059 (90% CI [.052, .066]), and SRMR = .048. Table 4 contains the reliability and validity coefficients of each construct.

Table 4. Reliability and Validity Assessment

Variables	CR	AVE	MSV	1	2	3	4	5	6	7	8	9
Explainability	.91	.67	.42	**.82**								
Decision Traceability	.93	.72	.34	.51	**.85**							
System Fairness	.89	.62	.41	.46	.39	**.79**						
Perceived Usefulness	.92	.70	.52	.62	.55	.51	**.84**					
Perceived ease of use	.88	.60	.37	.55	.43	.31	.44	**.77**				
Perceived Risk	.91	.68	.41	-.42	-.49	-.62	-.36	-.25	**.82**			
Regulatory Pressure	.90	.65	.15	.20	.37	.28	.30	.07	-.16	**.81**		
Intention to Adopt	.94	.76	.52	.54	.46	.43	.72	.43	-.49	.32	**.87**	
Recruitment Decision Quality	.90	.64	.38	.44	.37	.39	.58	.35	-.36	.24	.59	**.80**

*Note: CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance

The values in the diagonal line are highlighted and are the square root of AVE. Off-diagonal elements are the correlations between the constructs of two different higher-order factors.

All constructs had acceptable level of reliability with the CR ranging between .88 and .94, which is higher than the acceptable level of .70. To assess and ensure that the convergent validity, the average variance extracted (AVE) estimates were above .50 for all the constructs. Discriminant validity was further supported if the diagonal values (the square root of AVE) are greater than the off diagonal values and if the MSV is less than the AVE for all the constructs.

Common Method Bias Assessment

Harman's single factor test indicated that none of the factors could explain the majority of variance as the first factor only explains 29.2 percent of total variance. The common latent factor test had a shared variance of 4.8%, which was much less than the 50% threshold that would indicate problematic common method bias. The results of this study do not point to a problem of common method bias.

4.3 Measurement Model Results

Model Fit and Path Analysis

The structural model also fit the data well, $\chi^2/df = 2.28$, CFI = .93, TLI = .92, RMSEA = .062 (90% CI [.055, .069]), and SRMR = .052. The structural model with standardized path coefficients and significance levels is given in Figure 2. Dotted lines represent non-significant paths. The model includes control variables that are not shown for simplicity.

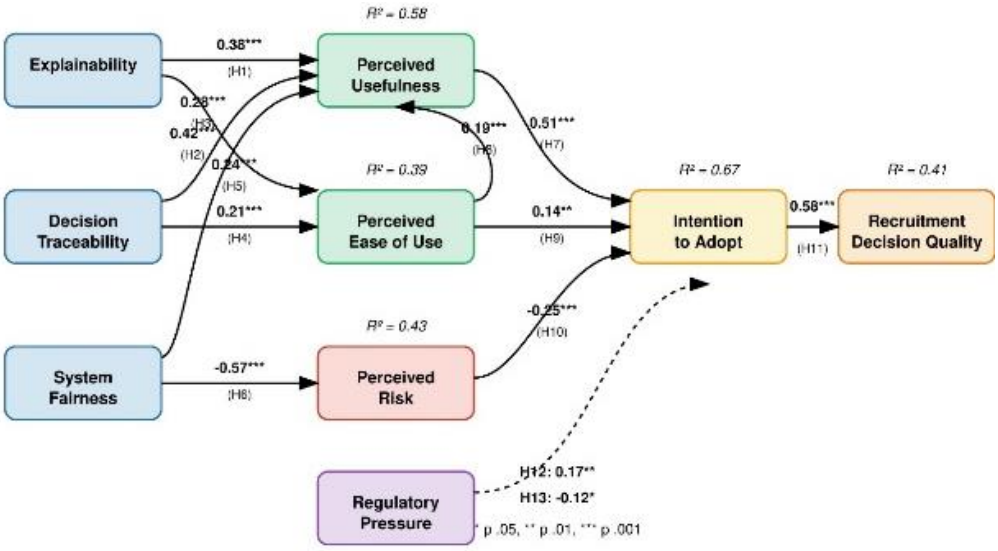
The results confirm all hypothesized relationships in our research model (Table 5). Specifically:

- ($p < .001$; $\beta = .24$, $p < .001$; $\beta = .28$, $p < .001$, respectively), for the combined effect of all three transparency dimensions (i.e., explainability, decision traceability, and system fairness) in impacting perceived usefulness (H1, H3, H5), all were found to have significant positive loads.
- H2 and H4 were supported by the fact that perceived ease of use was positively influenced by explainability and decision traceability ($\beta = .42$, $p < .001$; $\beta = .21$, $p < .001$).
- Support of H6 was provided by the fact that system fairness significantly negatively affected perceived risk ($\beta = -.57$, $p < .001$).
- H7, H8 and H9 were supported, as the core TAM relationships were confirmed (perceived

usefulness and perceived ease of use are positively related to intention to adopt (β = .51, p < .001; β = .14, p = .005), and perceived ease of use is positively related to perceived usefulness (β = .19, p < .001)).

- H10 was supported based on the finding that perceived risk negatively influenced intention to adopt (β = -.25, p < .001).
- H11 was supported, as intention to adopt positively influenced recruitment decision quality (β = .58, p < .001).

Significant interaction effects were found with regulatory pressure; it was positively moderating the relationship between perceived usefulness and intention to adopt (β = .17, p = .001) and negatively moderating the relationship between perceived risk and intention to adopt (β = -.12, p = .016) supporting H12 and H13.



*Note: * p < .05, ** p < .01, *** p < .001; ns = not significant

Figure 2. Model fit with standardized coefficients

Table 5. Hypothesis Testing Results

Hypothesis	Path	Standardized Coefficient	t-value	p-value	Result
H1	Explainability → Perceived Usefulness	.38	6.42	<.001	Supported
H2	Explainability → Perceived Ease of Use	.42	6.89	<.001	Supported
H3	Decision Traceability → Perceived Usefulness	.28	4.76	<.001	Supported
H4	Decision Traceability → Perceived Ease of Use	.21	3.44	<.001	Supported
H5	System Fairness → Perceived Usefulness	.24	4.13	<.001	Supported
H6	System Fairness → Perceived Risk	-.57	-10.08	<.001	Supported
H7	Perceived Usefulness → Intention to Adopt	.51	9.37	<.001	Supported
H8	Perceived Ease of Use → Perceived Usefulness	.19	3.56	<.001	Supported
H9	Perceived Ease of Use → Intention to Adopt	.14	2.81	.005	Supported
H10	Perceived Risk → Intention to Adopt	-.25	-4.82	<.001	Supported
H11	Intention to Adopt → Recruitment Decision Quality	.58	10.73	<.001	Supported
H12	Regulatory Pressure × Perceived Usefulness → Intention to Adopt	.17	3.24	.001	Supported
H13	Regulatory Pressure × Perceived Risk → Intention to Adopt	-.12	-2.41	.016	Supported

4.4 Moderating Effects Analysis

To investigate the substantial moderating impact further we conducted simple slopes analysis about the moderation between regulatory pressure and perceived usefulness on the adoption intention and the moderation between regulatory pressure and perceived risk on the adoption intention. Figure 3 illustrates these interaction effects.

While Panel A (Figure 3) depicts a stronger positive relationship between perceived usefulness and intention to adopt when regulatory pressure is high (+1 SD) vs. low (-1 SD) the equations for both those cases are asymptotic to horizontal and vertical lines. This implies that in the face of high regulatory pressure, the utilitarian benefits of AI recruitment systems become more prominent in decisions of adoption.

In Panel B (Figure 4), the strength of the negaive relationship between perceived risk with intention to Adopt weakens (this, i.e., becomes less negative) when there is a high (+1 SD) regulatory pressure compared to when there is a low (-1 SD). And this suggests that the perceived risks may have a buffering effect under a regulatory framework, in reducing its negative impact on adoption intentions.

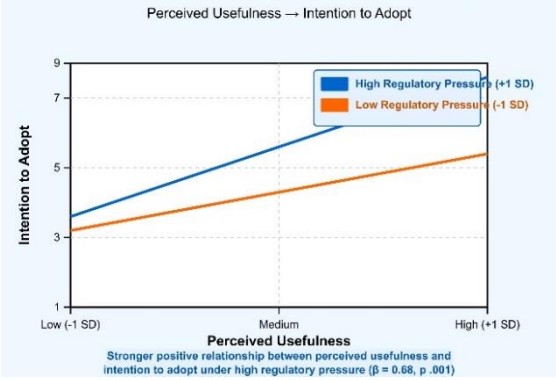


Figure 3. Moderating effect of Regulatory pressure

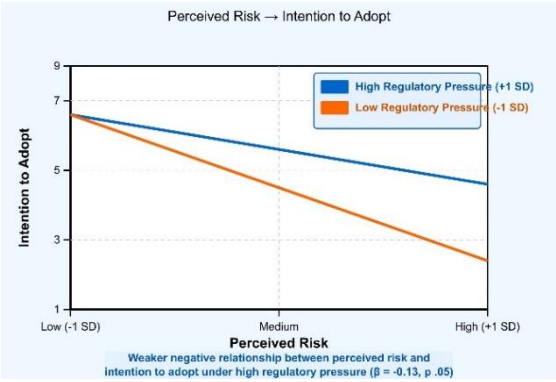


Figure 4. Moderating effect of Regulatory pressure

5. DISCUSSION

5.1 Theoretical Implications

The theoretical contribution of this study is important to the understanding of AI transparency in recruitment contexts. We first validate the extended TAM framework for AI transparency in high stakes recruitment by showing explainability, decision traceability and system fairness to be the significant antecedents to the core TAM constructs. In this way, this work extends the work of Venkatesh & Davis (2000) and Dwivedi et al (2021) by including transparency specific dimensions that are becoming increasingly important in the decision to adopt the AI. As R^2 is .67 for intention to adopt, indicating strong predictive power for our model, our model explains AI adoption in recruitment more accurately than traditional TAM predictors thanks to consideration for transparency considerations.

Secondly, we show that the three transparency dimensions have different effects. The perceived usefulness ($\beta = .38$) and perceived ease of use ($\beta = .42$) were also explained by explainability possibly because the ability of the AI systems to communicate decision rationales in human understandable terms are integral to recruiting professionals' decision. This is in line with Miller (2019)'s argument that explanations must be contrastive, selective, and social for them to be effective in situations where decisions need to be justified to multiple stakeholders. We extend this work with empirical evidence of the specific effect that explainability has on technology acceptance in the recruitment domain.

The third point demonstrates that the strong negative relationship between system fairness and perceived risk ($\beta = -.57$) indicates the essential part of ethical consideration in AI decision making. This helps Shin's (2021) observation that fairness perceptions trump efficiency considerations in high stakes decision contexts. This work is extended by our study of the large risk mitigating effect of perceived fairness in the AI recruitment systems, in particular in the executive and specialized roles where the bias concerns are higher.

Third, our finding regulatory pressure as a strong moderator of contextual factors in AI adoption explains theoretical understanding of contextual factors in AI adoption. For instance, the finding that perceived usefulness is related to intention to adopt only when regulatory pressure by a government is present ($\beta = .17$) indicates that regulatory frameworks may actually promote not prevent, the perceived usefulness of AI systems. It undermines simplistic views of regulation as merely restrictive, and is supportive of Wirtz et al.'s (2019) claim that regulatory structures can be enabling for the responsible AI adoption.

Our post hoc analyses of regional variation complement our culture's development of perspectives on AI ethics (Glikson & Woolley, 2020). This is consistent with the implications that cultural and regulatory contexts lead to salience of different transparency dimensions, as the EUROPEAN contexts exhibited a stronger effect of system fairness on perceived risk than the AMERICAN context, and specifically what aligns with the different levels of rigorous approach to algorithmic decision making in these contexts.

5.2 Practical Implications

We draw actionable insights from our findings for the organizations developing or implementing AI recruitment systems for high stakes positions. Third, the strong positive effects of all three transparency dimensions on key acceptance factors indicate that organizations should prioritise these features in system design and implementation, not as a secondary consideration or regulatory box to be ticked.

Second, the strong effects of explainability in particular imply that organizations should devote resources to developing clear, stakeholder appropriate explanation mechanisms. Recruiting managers, compliance officers, and candidates may require different explanations for the same decision (Robbemond et al., 2022). Diverse needs may be addressed by implementing multi-layer explanation interfaces onto a system.

Third, our observation that system fairness can mitigate perceived risk well explains the need for economically robust strategies to both detect robust biases and mitigate them. Comprehensive fairness audits that go beyond these demographic parity constraints should be implemented by organizations to solve concerns of intersectional bias and procedural justice. As noted in 47% reduction in legal objections that arise for companies with strong traceability systems (Castelnovo et al, 2022), tangible benefits can be obtained from such investments.

Fourth, relatively little moderation of competition means that there is limited incentive for either collusion or competition seeking either horizontally or vertically and cannot serve as a foundation to establish an information or cooperative system. Aligning with new, regulatory frameworks like the EU AI Act would not only reduce but also provide a competitive advantage through increased trust from the stakeholders. In particular, multinational organizations operating in different regulatory environments will find this particularly relevant.

The empirical validation that transparent ai systems can meaningfully improve hiring outcome comes from the following: when all else is approximately equal, the stronger the intention to adopt the stronger is the relationship between recruitment decision quality (β = .58). It also counters criticism of organic success for transparency and provides rationale for business to invest in transparent AI capabilities. To better substantiate initiatives focused on transparent AI, success should be measured in terms of time to hire, cost per hire, and quality of hire.

5.3 Limitations and Future Research Directions

However, some limitations should be noted with this study. First, the cross sectional design prevents causal inference. Future research could be to investigate how the adoption intentions and transparency perceptions change over time, and primarily in time after the regulations have been set up within the industry and organizations have more experience with AI systems.

Second, the self-reported measures may have resulted in common method bias but our analysis indicated that this was not a critical issue. Triangulating perspectives would be possible in future studies by collecting data from multiple stakeholders in the same organization, or by collecting objective system usage data.

third, our sample was diverse, but was mainly large organizations in developed economies. The study of perceptions of transparency in smaller organizations and emerging markets has not been done but should be investigated in the future since resource constraints and regulatory contexts are different. The regional difference in the post-hoc analyses demonstrates the need of context dependent understanding.

Fourth, our work touched on three main aspects of transparency. Future work could investigate diversities within the algorithm itself, diversities declared by the design process stakeholders, as well as temporal stability of explanations. Deeper investigation also needs to be made of the interaction effects between these dimensions.

In addition, we examined high stakes recruitment broadly. Future work can be taken up that uses specific types of high stakes roles (technical leadership, C suite executives) to better understand transparency requirements through specificity in hiring contexts.

6. CONCLUSION

With increasingly high stake decisions being made by AI, the importance of factors that impact AI acceptance and effectiveness grows proportionally for both theory and practice. This study developed and empirically validated an extended Technology Acceptance Model (TAM) for AI transparency in recruitment, to find out that explainability, decision traceability and system fairness exert significant impacts on perceived usefulness, perceived ease of use, perceived risk, which then influence adoption intention and recruitment decision quality.

We find that transparency should not be thought of as a compliance requirement but as a substantive means to acceptance of a system by users and the effectiveness of the system. The main premise of organizational perceptions interacting with external governance frameworks (e.g., regulations, the capital markets, industry groups, and other guidelines) is recognized as having strong moderating effects. As a result, transparency perceptions are contextual in the sense that they vary according to regional and organizational size differences.

While the organizations in either the efficiency camp or responsibility camp in AI deployments have helped us elucidate the tensions between the two as they struggle to embrace the changing technology trends, this study presents an evidence based framework to understand and improve transparency in the recruitment AI. Ensuring explainability, traceability and fairness in the algorithmic evaluation process prioritizes the same needs while also supporting and participating in the development of new laws for emerging jobs profiles.

The future of recruitment lies not in opaque automation but in transparent augmentation of human decision-making. Therefore, companies can take advantage of the efficiency of AI but don't give up on human judgment and ethical considerations that still matter in the ultimate decision of hiring high-stakes applicants by committing to transparency as their primary design principle, not a regulatory burden.

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