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ALGORITHMIC FAIRNESS AND HUMAN OVERSIGHT A CROSS-CULTURAL FRAMEWORK FOR ETHICAL ARTIFICIAL INTELLIGENCE IN HUMAN RESOURCE MANAGEMENT

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ABSTRACT

Artificial intelligence has changed the way organizations recruit their staff. This change raises ethical questions related to fairness especially when cultures are different. This paper develops a cultural framework which connects algorithmic fairness with human supervision. The study uses a survey that was filled out by 412 HR professionals from Europe and the Arab world. The collected data were supported by a Delphi panel that was composed of 18 AI ethicists. The findings reveal that culture can affect ethical expectations. In addition to that, the study found that the participants from (Arab) collectivist countries valued relational transparency, while the participants from (Western) individualist cultures considered procedural justice as a top priority. More importantly, both groups believed that the most ethically accepted model that organizations trust should combine both: AI systems and the supervision of humans. Thus, the paper concludes that fairness and accountability are best achieved when technology serves humans rather than replaces them.

KEYWORDS: Governance; Cross-Regional Ethics; Cultural Diversity; Accountability; Transparency.

1. INTRODUCTION

Over the past few years, artificial intelligence (AI) has greatly influenced how organizations manage their staff. Brynjolfsson and McAfee (2017) pointed out that Algorithms now assist in screening applicants. They can predict employee turnover and evaluate their performance. What once depended on human intuition is increasingly influenced by predictive models now" (p.4). While many organizations believe that AI is more efficient and consistent, it raises important questions regarding fairness (Jussupow et al., 2021).

In general, AI can make HR decisions more transparent and less biased. Yet, some think that automated processes may re-produce inequalities. Some of the data that were used to train AI fund that automated models may reflect existing social biases. In other words, algorithmic systems can unintentionally discriminate against marginalized groups (Bogen & Rieke, 2018; Raghavan et al., 2020). The issue is not only technical but ethical: who is accounted responsible when an automated decision harms someone? As Whittlestone et al. (2019) argue, individual developers are not the only people who are deemed accountable for AI biases; organizations have the same responsibility.

1.1. The Ethical Crossroads of AI In HRM

Human resource management (HRM) governs how people are valued in the workplace. The introduction of AI in HRM has led technology to interfere in one of the most human-centered domains in any organization (Meijerink et al., 2021). Although automation is fast and efficient, it threatens to cancel empathy and sensitivity that good HR requires.

The challenge is even greater in international organizations where ethics are not universal. In such organizations, cultural contexts can deeply influence fairness and respect (Hofstede, 2011). In many Western organizations, fairness emphasizes procedural equality; collectivist organizations, on the other hand, emphasize harmony and collective responsibility (Leung & Bond, 1984). For instance, a system that anonymizes a candidate's data might appear neutral in Europe but impersonal in Arab cultures (Al-Khatib et al., 2002).

1.2. From Fairness as a Code to Fairness as a Culture

In AI research, fairness is often treated as a technical metric that aims to achieve a balanced representation (Mehrabi et al., 2021). However, for humans, fairness is a social and moral obligation. Unlike AI, employees and managers experience fairness not through code, but rather through transparency and mutual respect (Rawls, 1971; Colquitt, 2001).

Floridi and Cowls (2012) argue that ethical AI requires both *beneficence* (acting for the good of humanity) and explicability (i.e. people can challenge AI decisions). Similarly, Jobin et al. (2019) found that transparency and human oversight are the most important principles for trustworthy AI. The problem, however, is that these principles often lack clarity. Additionally, the level of human involvement that is "ethical" is not well-defined. Bankins (2021) addressed this gap through her "human-in/on/out-of-the-loop" framework. She showed that oversight can range from direct control to full autonomy.

1.3. Why Culture Matters in AI Ethics

"Although AI ethics has become a global concern, much of the discourse reflects Western moral philosophy which is grounded in autonomy, individual rights, and procedural justice" (Hagendorff, 2020, p.110). However, other ethical traditions emphasize community, responsibility, and moral balance. "In many non-Western contexts, legitimacy stems from relationships rather than contracts, and moral reasoning is collective rather than individual" (Al-Khatib et al., 2002, p.102).

In the Arab world, for example, fairness is tied to the preservation of social harmony (Elamin & Omair, 2010). Thus, an HR algorithm that mechanically ranks candidates can be seen as dehumanizing rather than objective. Thus, understanding these moral frameworks is critical for organizations which seek to use AI responsibly in different countries and cultures. Without taking culture differences into account, AI systems can damage the trust that these organizations aim to build (Jobin et al., 2019).

1.4. Objectives And Research Questions

Nowadays, many organizations have AI-driven HRM. This paper seeks to develop a cross-cultural ethical framework that connects algorithmic fairness to human oversight in these organizations.

The study aims to answer the following questions:

1. How do HR professionals who work in different cultural contexts perceive fairness when AI assists in making decisions?
2. What forms of human oversight can be 'ethical' in these different contexts?

To answer these questions, the study built a design that combines two methods: a cross-regional survey, and a Delphi expert panel. The survey aims to obtain the perspectives of HR professionals in Europe and the Arab world (n = 412). On the other

hand, the Delphi panel gives reflects the perceptions of 18 AI ethics specialists. This approach will offer a solid account of how ethical is using AI in managing organizations in different cultures.

1.5. Significance Of the Study

This research contributes to 'ethical AI' field in three different ways. First, it argues that algorithmic fairness and human oversight are not universal. Rather, they are practices that are determined by cultural morals. Second, it transforms ethical principles into procedural justice that HR leaders can operate. Third, it offers a 'culturally adaptive governance' which may guide organizations when they use AI responsibly. At the same time, it tries to maintain justice in different cultural regions.

Ultimately, this study argues that ethical AI is not concerned only with eliminating bias. It affirms the moral purpose of technology. Fairness, transparency is not just algorithmic challenges; it is a human value that must be protected through ethical management. As AI continues to restructure the future of work, it is important that these technologies do not replace humans.

2. LITERATURE REVIEW

2.1. Algorithmic Fairness and the Illusion of Objectivity

AI entered was first used in human resource management (HRM) to eliminate bias when humans make decisions. Managers believed that AI could evaluate candidates without the bias that humans may have. So, they hoped that AI would be able to hire and promote people based purely on merit (Brynjolfsson & McAfee, 2017).

But that hope could not be fully achieved. As HR started using AI in its processes, researchers found that algorithms had sometimes re-produced the bias that they were meant to prevent. Raghavan et al. (2020) pinpointed that the root of the problem lies in the data. HR data often reflect social inequalities, gender imbalances or cultural preferences. When these data are used to train AI, they appear as 'objective' recommendations.

This raises an important question: what does fairness really mean when it is transformed into codes? Binns (2018) proposes that AI fairness is not merely a mathematical equation. It is a moral responsibility. Programmers may be interested in technical criteria like statistical equality. However, people may not. When an employee feels that s/he was unfairly treated by a machine, it is not the data they blame. Instead, they blame the humans behind the decision.

As Colquitt (2001) contends, fairness has several dimensions. It includes: "'Procedural Justice' which refers to the fairness of the process; 'Distributive Justice' which indicates the fairness of outcomes)' and 'Interactional Justice' which mean that the treatment and communication are fair for everyone" (p.390). These dimensions indicate that algorithmic fairness must not be completely tied to code. Rather, it must include the morals of the people who are affected by it.

2.2. Human Oversight: Keeping Humanity in the Loop

When we give machines more control, we need to have more human oversight. In the context of HRM, where decisions can shape careers, human judgment becomes an ethical concern rather than a technical issue (Floridi et al., 2018). Therefore, Bankins (2021) proposed three categories to describe the levels of human involvement in AI systems. The researchers called the first category 'Human-in-the-loop' where people make or approve each decision. In their second category, 'Human-on-the-loop', humans supervise and intervene when necessary. In the third category, 'Human-out-of-the-loop', systems operate independently. These categories are important because they determine how much control humans must have.

Previous studies show that when people trust AI too much, they comply to its outputs without questioning. By contrast, when systems are controlled by humans, their efficiency suffers. Then, the challenge is not whether to involve humans or not, but how to involve them. Therefore, organizations' oversight combines machine efficiency with human empathy and moral reasoning (Dellermann et al., 2019).

In conclusion, what 'oversight' means is culturally dependent. In some societies, compliance to technology is seen as progress; in others, it is not. In collectivist contexts, for example, human oversight may be considered a shared moral duty rather than individual control.

2.3. Culture And the Moral Geography of Fairness

Fairness does not mean the same thing everywhere. In Western cultures, fairness often revolves around individual rights and equality before the law. In collectivist societies, fairness is grounded in social harmony and shared accountability (Hofstede, 2011; Leung & Bond, 1984). These differences shape how AI ethics are practiced.

For instance, research in Arab contexts reveals

that fairness is tied to the idea of moral balance; i.e. an ethical order that values relational justice over procedural justice (Al-Khatib et al., 2002; Elamin & Omair, 2010). In such situations, a hiring algorithm that treats every applicant equally may not be seen fair at all. Instead, fairness may be measured through empathy and community trust.

This cultural diversity challenges the 'global' AI ethics framework. Jobin et al. (2019) describe this as Ethical Monocropping. This refers to applying western morals to non-western societies. Consequently, when ethics are regulated globally, they risk becoming detached from the cultures and communities they serve.

Floridi and Cowls (2022) therefore call for context-sensitive AI Ethics. It means that ethics should not only value universal human rights, but they should take into account local ones. HRM should, therefore, recognize treat fairness and accountability differently across different cultural settings.

2.4. Organizational Justice in the Age of Algorithms

There are five types of Justice. First 'organizational justice' does not only require technical fairness. Colquitt (2001) showed that in addition to outcomes, employees also care about process of hiring. 'Procedural justice', on the other hand, concerns the fairness of the algorithm's design. Decisions should be made consistently without any hidden bias. By contrast, 'distributive justice' underlines that AI outcomes such as promotions or hiring should be fair to all groups. The fourth type is 'interpersonal justice' which refers to how individuals are treated when AI systems make decisions. Finally, 'informational justice' refers to transparency. It makes sure that employees understand how and why an AI system made its hiring recommendations (Holstein et al., 2019; Jussupow et al., 2021).

In all these kinds of justice, trust should be the connector. Glikson and Woolley (2020) pinpoint that trust in AI is not built through accuracy alone; it should be combined with morals. People must feel that the systems reflect the ethical identity of their organizations. In HRM, such trust is reinforced when employees know that human judgment remains part of the decision process. As Meijerink et al. (2021) put forward, employees are more willing to accept AI recommendations when they see them as tools that support human discretion rather than replace it.

2.5. Bridging The Divide: Toward A Cross-Cultural Ethical Framework

Recently, fairness, oversight, and culture have been merged into a more holistic approach that is linked to ethical AI. Bankins (2021) proposed an ethical decision-making model that combines the moral sensitivity of HR tasks with the appropriate level of automation. Nevertheless, her model emerged from an Australian context and therefore remains largely untested in other different cultural settings.

Building on Bankin's model, the present study argues that algorithmic fairness, human oversight, and cultural context are interdependent elements of ethical AI. The reason for such interdependence is that when fairness is detached from culture, it may become abstract. When oversight overlooks culture, it may impose irrelevant notions of control. However, when oversight and culture are interrelated, they form a balanced ethical system that considers the global principles and the local morals.

In essence, ethical AI is not about feeding machines with global morals. It is about designing technologies that respect the ethical diversity of humans. This research studies how professionals of different regions perceive fairness and oversight in order to build a framework that is globally and locally relevant.

3. THEORETICAL FRAMEWORK

3.1. Foundations Of Ethical AI In Human Resource Management

Many programmers and HR professionals assume that they can design technology in a neutral way. Yet, as studies show, algorithms can never be neutral. Floridi et al. (2018) believe that "They reflect the moral, social, and organizational choices of the people who build and deploy them. AI systems embody the values of their creators, and these values ultimately shape how technology interacts with society" (p. 701).

In human resource management (HRM), AI systems screen applicants first and rank their curriculum vitae. Additionally, they evaluate employee performance. These functions may seem technical, but in practice they affect the inclusion of some candidates and the opportunities they may get. Bankins (2021) was among the first to argue that "the ethical challenge in AI-driven HRM lies in aligning technology with the moral sensitivity of the task. The more ethically sensitive a decision is- such as promoting, disciplining, or dismissing an employee- the greater the need for human judgment and oversight" (p. 849).

Building on this alignment, this study maintains that ethical AI in HRM is a question of task sensitivity

and cultural interpretation. In some contexts, delegating AI to make hiring decisions may seem progressive; in others, it may appear disrespectful. In a nutshell, ethics, like fairness, cannot be purely technical. Rather, it has cultural and relational dimensions.

3.2. Connecting Fairness, Oversight, And Culture

The Cross-Cultural Ethical AI Framework (CCE-AIF) proposed in this study has three related dimensions:

1. Algorithmic Fairness: it refers to how just and transparent the AI's outcomes are.
2. Human Oversight: it refers to how much humans control the AI decisions.
3. Cultural Ethics Context: it refers to how local morals can shape fairness and oversight.

These three dimensions are interacting elements because algorithmic fairness somehow shapes trust. However, the meaning of 'fairness' depends on cultural ethics. Similarly, human oversight builds accountability, but the right level of oversight differs in different societies. In one culture, strong oversight may signal integrity, while in another, it might imply lack of trust.

1. Algorithmic Fairness: Beyond Technical Balance

Fairness in algorithms is often treated as a mathematical property that tries to ensure that decisions do not disadvantage certain groups (Binns, 2018; Mehrabi et al., 2021). Yet, fairness in organizations is something that is lived, not calculated. It is about whether people feel respected and whether the system is congruent with shared moral expectations. As Colquitt (2001) notes, fairness has several dimensions: fairness of process, fairness of outcomes, and fairness of treatment.

In HRM, algorithmic fairness requires transparency about how decisions are made. Nevertheless, it requires empathy as it recognizes that people are more than the data points which is used to represent them. Therefore, a system can be technically unbiased yet unfair if it dehumanizes those it evaluates.

2. Human Oversight: Ethics In the Loop

Human oversight is what keeps technology morally established. It ensures that final decisions are not just efficient but also justifiable in human terms (Rahwan, 2018). Oversight also creates a space where empathy, discretion, and accountability can intervene when algorithms fail.

Bankins (2021) points out that there are three levels of oversight:

- Human-in-the-loop, where people control critical decisions;
- Human-on-the-loop, where humans supervise and intervene when necessary;
- Human-out-of-the-loop, where decisions are largely made by AI.

It is noteworthy that in 'human-on-the-loop', AI provides analytical power but humans supervise it and intervene when necessary. Yet, what counts as 'adequate oversight' depends on the cultural. In some societies, people trust technology blindly; in others, morality requires human involvement. Oversight, therefore, is not only technical, but it is also moral.

3. Cultural Ethics Context: Where Morality Meets Design

Cultural ethics refers to a collection of morals through which people interpret fairness and accountability. Hofstede (2011) proposed the cultural dimensions of 'Individualism vs. Collectivism' and 'Power Distance'. These dimensions can help explain why ethical expectations differ across societies. In collectivist cultures, decisions are often judged by how they preserve harmony and shared responsibility in the organization. In individualistic cultures decisions are judged by how they protect autonomy and procedural equality (Markus & Kitayama, 1991).

This means that the same AI system may be perceived as ethical in one culture and unfair in another. For example, in Arab business environments, ethical legitimacy is often tied to moral balance and the preservation of dignity in relationships (Al-Khatib et al., 2002; Elamin & Omair, 2010). An impersonal AI tool might therefore be seen as undermining, rather than upholding fairness.

3.3. The Cross-Cultural Ethical Ai Framework (Cce-Aif)

The CCE-AIF integrates these three dimensions into a single, dynamic model (see Figure 1 below). It proposes that 'Perceived Ethical Legitimacy (PEL)' is the result of the interaction of Algorithmic Fairness (AF), Human Oversight (HO), and Cultural Ethics Context (CEC).

In this model:

- Algorithmic Fairness is the foundation of trust.
- Human Oversight guarantees accountability and empathy.
- Cultural Ethics Context determines the interpretation of fairness and oversight.

When these three dimensions are integrated, employees and managers are more likely to view AI as morally legitimate. However, when they conflict (e.g. when global fairness clash with local norms) trust and acceptance weakens.

In conceptual terms:

PEL = f(AF × HO × CEC)

Thus, ethical legitimacy depends not only on fairness itself, but on how fairness and oversight meet cultural expectations.

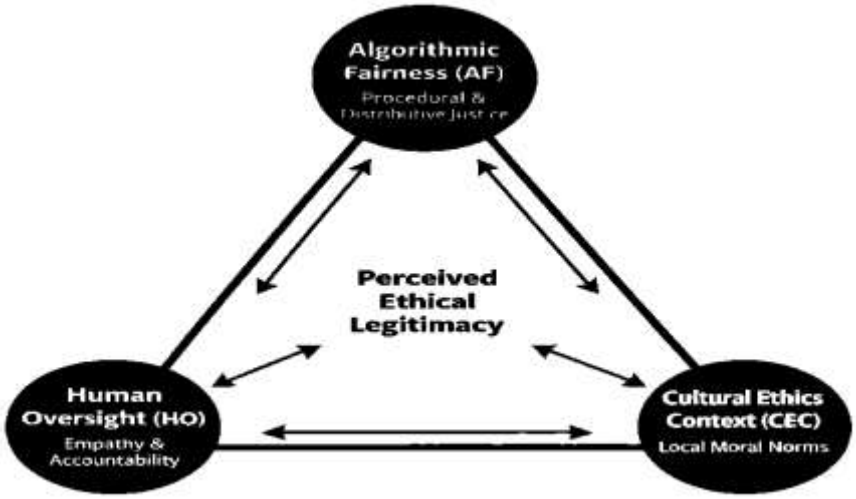

Figure 1: The Cross-Cultural Ethical AI Framework Model (CCE-AIF).

3.4. Theoretical Foundations

The framework obtains its strength from three theoretical traditions:

1. Organizational Justice Theory (Colquitt, 2001): "Fairness is not a single value but a family of moral judgments; procedural, distributive, interpersonal, and informational. These dimensions translate algorithmic fairness from code into human experience" (p. 395).
2. Socio-Technical Systems Theory (Trist & Bamforth, 1951): "Organizations function best when technical systems and social systems co-evolve". Ethical AI must therefore integrate technological efficiency with what humans mean.
3. Cultural Relativism in Ethics (Hofstede, 2011; Markus & Kitayama, 1991): Ethical reasoning is culturally situated". Therefore, there is no universal moral algorithm but each culture has its own interpretations of fairness and responsibility.

Together, these traditions frame ethical AI as a continuous conversation between people, machines, and values.

3.5. Theoretical Propositions

From this framework, several propositions can be drawn:

- P1: Perceptions of fairness in AI-driven HRM differ significantly across cultures, hence reflecting distinct moral priorities.
- P2: Moderate human oversight (human-on-the-loop) gives the highest ethical legitimacy across cultural settings as it balances autonomy and accountability.
- P3: Cultural ethics moderate the relationship between fairness and ethical legitimacy; that is, fairness is judged relative to cultural expectations rather than universal norms.
- P4: Organizational trust mediates the link between human oversight and ethical acceptance. Therefore, it reinforces the moral relationship between people and technology.

These propositions set the foundation for the mixed-method research design described in the next section.

4. METHODOLOGY

4.1. Research Design

How people perceive fairness in AI-driven HRM is more than mere statistics. It calls for considering certain patterns *and* perspectives. To understand the moral and cultural interaction, this study adopts a mixed-method design which combines quantitative and qualitative analyses.

The research consists of two phases. The first one is a survey that was conducted on HR professionals from Europe and the Arab world. The survey measures their perceptions about algorithmic fairness and human oversight. The second is a Delphi

expert panel, which aimed to obtain opinions from the academia and industry in order to interpret the findings. Finally, the design follows what Creswell and Plano Clark (2018) call a Sequential Explanatory Approach. It means that the survey outcomes can make it possible for the Delphi panel to contextualize the patterns found in the outcomes.

4.2. Sampling And Participants

Phase I – Cross-Regional Survey

The survey obtained responses from 412 HR professionals who work in education, manufacturing, and technology. Almost half of the participants are from Europe (n = 204) while the other half come from the Arab world (n = 208). This balance between the two groups allows for cultural comparison. Furthermore, it ensures representation from different organizations.

The participants, who were 25 to 58 years old, had an average of 10 years of HR experience. They held various positions including HR generalists (35%), senior managers (28%), recruitment specialists (21%), and ethics or policy officers (16%). Fifty-eight percent of them were women. The diversity of this sample was important for the analysis since it reflected different perspectives on how AI can affect fairness and decision-making at work.

Phase Ii – Delphi Expert Panel

The study also had a Delphi panel of 18 international experts. The panelists included AI ethicists, HR technology specialists, and scholars of different cultural management. They come from four Arab countries: Jordan, Saudi Arabia, the UAE, Egypt; and three European countries: France, Germany, and the UK.

Unlike focus groups, the Delphi panel does not depend on discussion. Instead, it aims to reach consensus through several rounds of reflection. Each expert reviewed the findings independently and provided their feedback. Later, the feedback was re-circulated for further modification. In this way, the process helped to obtain agreements based on logic and cultural differences.

4.3. Instruments And Measures

Survey Design

The survey was composed of four components: algorithmic fairness (AF), human oversight (HO), cultural ethics context (CEC), and perceived ethical legitimacy (PEL). The survey items were rated on a Likert scale of five points (from 1 = strongly disagree to 5 = strongly agree).

The sample items included some of the following:

- "The AI system used in our recruitment process treats all candidates equally, regardless of their background." (AF)
- "Human judgment is appropriately integrated into AI-driven HR decisions." (HO)
- "In my culture, fairness in decision-making is defined by maintaining social balance rather than strict equality." (CEC)
- "AI decisions in our organization are ethically trustworthy." (PEL)

The instrument combined adapted scales from existing literature (Colquitt, 2001; Bankins, 2021; Hofstede, 2011) with newly developed items reflecting cross-cultural ethics. The Cronbach reliability test showed strong internal consistency across the four components/ constructs ($\alpha > 0.83$). The exploratory factor analysis confirmed the four components as it explained 70% of the responses.

Delphi Protocol

The Delphi study was carried out in three rounds over six weeks.

- Round 1: Each expert reviewed the summary of the findings and commented on the them.
- Round 2: They rated the validity of fairness types and oversight levels on a 7-point agreement scale.
- Round 3: Finally, the group refined definitions and made recommendations on what they agreed upon (Agreement threshold was 75% and above).

The survey and the Delphi study made it possible to see how AI ethics could be adapted to make a balance between the universal principles and the local values in different cultural contexts.

4.4. Data Analysis Procedures

Quantitative Analysis

The survey data were analyzed using SPSS 29 and AMOS 28. The descriptive statistics gave general trends. The *t*-tests and multi-group (SEM) compared the perceptions across the two regions.

The measurement model demonstrated solid construct validity ($\chi^2/df = 2.41$, CFI = 0.94, RMSEA = 0.056).

Key relationships included:

- Algorithmic fairness was the strongest predictor of perceived legitimacy ($\beta = 0.61$, $p<.001$).
- Human oversight amplified fairness effects ($\beta = 0.29$, $p < .01$).
- Cultural ethics strengthened the fairness–

legitimacy relationship in collectivist contexts.

These results suggest that ethics in AI-driven HRM are should be culturally adjusted. This means that what is fair and trustworthy in one context may be considered unfair in another context.

Qualitative Analysis

The Delphi feedback was analyzed through thematic analysis (Braun & Clarke, 2006). There were three main themes:

1. Cultural interpretations of fairness: whether fairness refers to equality or to relational balance.
2. Ethical boundaries of automation: it defines the roles of machines and roles of humans.
3. Hybrid governance models: it supports the "human-on-the-loop" approach to keep humans engaged.

This Delphi analysis enhanced the quantitative findings by changing moral language into numbers.

4.5. Ethical Considerations

Because this study is concerned with ethics, it was designed in a way that followed the standards of academic integrity. All participants sent their informed consent. The study agrees with the 'European Commission's Ethics Guidelines for Trustworthy AI' (2019).

More importantly, the data collection considered cultural sensitivity issues. The survey was delivered in English and Arabic using back-translation was used to preserve meaning across languages. Questions were written in a way that takes into consideration cultural differences with regard to fairness and trust.

4.6. Integration And Validity

This research used quantitative and qualitative to have a comprehensive view of the ethicality of using AI in HRM decision. The Delphi panel explained the ethical reasoning behind the responses of the survey.

To ensure validity:

- Instruments were pilot-tested with a small group of HR practitioners.
- Expert feedback refined ambiguous items.
- Independent coders reviewed Delphi themes for consistency.

4.7. Limitations And Future Directions

This study has some limitations. First, the study was conducted in two culturally different regions: some Arab countries (Jordan, Saudi Arabia, the UAE, and Egypt) and some European countries (France, Germany, and the UK). So, the number of participating countries in each region was limited. Therefore, future research could be expanded to include additional Arab contexts, or Southern European nations. That would definitely strengthen the generalizability of the results.

Second, although the survey sample provided good quantitative data, it relied on measures that were self-reported. Future studies could improve it by collecting some organizational data, such as AI audit logs.

Third, the study data were collected from professionals and academics who had direct involvement in HRM. However, the employees themselves were not involved. When employees' opinions are included, it could add a value as they are the most affected party by the AI-driven HR systems. In spite of these limitations, the study provides an empirical foundation for understanding the morals of AI in HRM. By combining statistics with expert reflection, it emphasizes that the ethics of AI are not utterly technical. Rather, they should be social and cultural in order to show how fairness is seen in specific communities.

In that sense, this research offers a model for future studies which seek to balance technology with the cultural values.

5. RESULTS

5.1. Overview

This section presents the results of the study in order to explore how perceptions of algorithmic fairness, human oversight, and cultural ethics influence the validity of (AI) in human resource management (HRM).

As mentioned earlier, data were collected from 412 HR professionals: 208 from Arab countries and 204 from European countries. To support the survey data, a Delphi expert panel of 18 Arab and European participants, provided interpretive feedback. They helped to explain how fairness and accountability should be understood in different cultural contexts.

5.2. Descriptive Findings

Overall, participants in both regions expressed moderate positive perceptions of AI in HRM. In fact, there were some cultural differences between the European and Arab participants.

Arab participants scored slightly higher on all ethical dimensions, especially on the cultural ethics and human oversight. It is noteworthy that many Arab participants viewed oversight as a reflection of human care when making decisions. By contrast, European participants tended to emphasize procedural equality because they viewed fairness as

a question of system integrity.

These results indicate that there are two complementary views of AI fairness: one that preserves human dignity, and the another that values procedural fairness.

5.3. Structural Relationships

In both regions, algorithmic fairness was the most decisive factor of ethical AI. When people believed that AI decisions were unbiased, they were more likely to trust their organizations.

However, moral weight was stronger in the Arab countries ($\beta = 0.63$) than in the European ones ($\beta = 0.57$). For example, fairness had more moral weight in a country like Jordan, in which ethics is often interpreted through relational justice and human dignity.

Human oversight also played a significant role. In both regions, participants expressed greater confidence in AI systems when humans supervised HR processes. This effect was particularly clearer in the Arab sample who believe that moral responsibility cannot be fully achieved by machines.

The cultural ethics context was important in both groups. In the Arab world, fairness and oversight should interact. Put differently, ethical AI was best when humans remained accountable for the actions of technology.

5.4. Delphi Insights: Expert Reflections

Through three rounds, the experts agreed on six main themes.

1. Fairness Is Interpreted Through Culture

Experts agreed that fairness is not purely technical. Arab participants described it as "acting with integrity toward others,". European experts focused on transparent criteria and the right to appeal decisions. Both groups seek justice, but they approach it through different ethical views: The Arabs relational, and the Europeans procedural.

2. Human Oversight as Moral Factor

In both regions, participants described oversight not as a control mechanism but as an ethical tool. They repeated the idea of the "human-on-the-loop": people should remain involved to know when an AI decision is morally wrong, not just technically incorrect.

3. Trust Must Be Both Transparent and Intentional

Experts emphasized that information alone does not build trust. As one Arab ethicist expressed it, "Transparency tells us what the system did. Oversight tells us *why* it matters."

4. The Need for Ethical Fit

Experts from the Arab region stated that imported AI ethics frameworks often overlook local values. They called for 'culturally adaptive ethics' in order to ensure that systems respect collective responsibility and moral duty. They did not want the systems to replicate the Western individualist traditions.

5. Shared Accountability Between Humans and Machines

Rather than placing full trust in either AI or human judgment, participants suggested a hybrid model: machines for efficiency and humans for empathy. Therefore, ethical integrity will depend on the balance between them.

6. Ethical Governance as Continuous Dialogue

Experts agreed that ethical AI governance must be a living process, not a fixed code of rules. It should be a continuous interaction between technology, culture, and human judgment.

5.5. Integrating The Two Components

The results of the quantitative and qualitative findings reveal the following:

- Algorithmic fairness is the foundation of ethical legitimacy, but its meaning is filtered through culture.
- Human oversight enhances trust when it emphasizes moral values.
- Cultural ethics determine when they see it as *ethical* in the first place.

In Arab countries, these elements represent a relational-ethical model of AI governance. It is a model that sees fairness as a duty to others and oversight as moral presence. It, further, considers ethics as collective rather than individual.

On the other hand, European countries adopt a procedural model. Fairness is represented by transparency, equality, and accountability.

Eventually, neither model is better than the other; both stand for deep moral thinking.

5.6. Summary Of Key Findings

The main findings of the study are:

1. Although each region interprets it differently algorithmic fairness remains the strongest predictor of ethical legitimacy in both regions.
2. Human oversight reinforces trust in HR systems that are driven by AI.
3. Cultural ethics was crucial, particularly in

Jordan, where relational values determine the understanding of fairness.

4. The Delphi panel recommended having a hybrid model that combines 'algorithmic precision' with 'human empathy'.
5. The Cross-Cultural Ethical AI Framework (CCE-AIF) was found to have strong explanatory power. Consequently, it can be applied in different cultural settings.

5.7. Reflection

Ultimately, these findings reveal that the ethical validity of AI is a technological achievement and a moral accomplishment at the same time. In Arab countries, fairness is about honor and shared dignity, while in European countries, it is about consistency and procedural justice. Both views accept ethical confidence when technology is guided by human values. By combining quantitative and qualitative data and cultural understanding, this study found that responsible AI is rather human.

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