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EXECUTIVE SUMMARY

Workplace in the twenty-first century workplace is nothing like the traditional systems, they are going through some serious transformation/upgrade rapidly due to advancement of artificial intelligence (AI), machine learning algorithms, and data-driven decision systems. These practices are completely taking over the human resource management functions. These computational operations in HRM is referred to as Algorithmic HRM, this has changed the nature of work, changed the employees experience for the better, and aligns the responsibilities of HR professionals more with the organization's strategies. While algorithmic systems promise improved efficiency, objectivity, and scalability in managing human capital. AI also introduce a collection of previously left out challenges that carry large impact for employee well-being, organizational trust, and workplace equity.

This research project critically examines the challenges rooted in Algorithmic HRM with particular attention to the psychological and organizational functions that traditional HR practices has given less attention to. In the centre of this paper is the concept of emotional labour, which is theorized by sociologist Arlie Hochschild (1983) as the management of feeling to create a publicly observable facial and bodily display, which suggest that the work environments created by algorithms have become more complex to evaluate. When workers interact with customers through digital platforms which is monitored by AI, or when performance is evaluated by AI systems which is not capable of recognizing emotional context of the humans, the invisible psychological labour of emotion management becomes even more complex and it could be overlooked very easily by the organization.

Focusing exclusively on secondary data sources including peer-reviewed journal articles listed in Scopus and Web of Science, institutional reports from the International Labour Organization (ILO), McKinsey Global Institute, Deloitte, and World Health Organization (WHO), as well as landmark academic books and real-world case studies from platform economy organizations such as Uber, Amazon, and Swiggy, this study is based on a qualitative secondary research design which uses thematic synthesis methodology.

The analysis identifies six primary challenge areas in Algorithmic HRM: (1) algorithmic lack of transparency and the decline of procedural justice; (2) increased emotional labour demands in digitally supervised work environments; (3) the multiplication of algorithmic bias and partial decision-making; (4) the breakdown of psychological safety and organizational trust; (5) the systematic promotion of burnout through automated performance pressure; and (6) the shortcoming of existing HR governance frameworks in addressing these current risks.

Taking the challenges in the account, this study make an innovative theoretical contribution to overcome and manage the challenges by suggesting the Integrated Algorithmic-Human Emotional Balance Framework (IAHEBF). IAHEBF is a conceptual model which is designed to guide HR professionals and leaders in making the HR systems more coherent algorithmically and better equipped to handle all the possible situations, by doing so it protects human dignity, support emotional well-being, and maintain ethics in the governance of the organization. The framework takes in account the variables across four areas (1) algorithmic control parameters, (2) emotional labour dimensions, (3) organizational HR interventions, and (4) employee outcome indicators. These variables ensures that the HR systems remain theoretically grounded and also practically applicable in the real time scenarios. This framework ensures responsible and ethical algorithmic HRM across all the functions.

This study gives us findings which will be very incidental for future studies in this domain. The findings will be useful for HR researchers, policy makers, technology designers, and HR professionals and leaders working in the humanly aspects and ethical concepts of AI adoption in the dynamic workplace. Algorithmic processes are widely used in talent acquisition, performance management, workforce scheduling, and employee engagement. With the wide adoption it has become almost a necessity to design algorithmic systems which are more equipped with emotional intelligence, ethics, transparency and values that are core to the humans.

45

TABLE OF CONTENTS

FRONT MATTER	
Certificate	ii
Declaration	iii
Acknowledgement	iv
Executive Summary	v
Table of Contents	vii
List of Tables	ix
List of Figures	x
CHAPTER 1: Introduction	1
1.1 Background and Context	1
1.2 Evolution of HRM to Algorithmic HRM	3
1.3 Emotional Labour: Conceptual Foundations	7
1.4 Intersection of AI and Emotional Labour	10
1.5 Problem Statement	12
1.6 Research Questions	13
1.7 Objectives of the Study	14
1.8 Scope of the Study	14
1.9 Significance of the Study	15
CHAPTER 2: Literature Review	17
2.1 Emotional Labour Theory	17
2.2 Algorithmic Management Literature	20
2.3 Digital Work and Burnout	22
2.4 Comparative Analysis: Traditional vs Digital Emotional Labour	24
2.5 Thematic Synthesis and Research Gaps	26
CHAPTER 3: Research Methodology	29
3.1 Research Philosophy and Design	29
3.2 Nature of Study: Secondary Qualitative Research	30
3.3 Data Sources and Search Strategy	31
3.4 Inclusion and Exclusion Criteria	32
3.5 Analytical Technique: Thematic Synthesis	33
3.6 Reliability, Validity and Ethical Considerations	34
CHAPTER 4: Analysis, Discussion and HR Implications	36
4.1 Thematic Analysis: Core Findings	36
4.2 Algorithmic Opacity and Procedural Justice	38
4.3 Emotional Exhaustion in Digitally Monitored Work	41

4.4 Algorithmic Bias and Discriminatory Outcomes	44
4.5 Erosion of Psychological Safety and Trust	47
4.6 Burnout, Fatigue and Cognitive Overload	49
4.7 Organizational Responses and HR Interventions	52
4.8 Limitations of the Analysis	56
CHAPTER 5: Proposed HR Framework (IAHEBF)	57
5.1 Framework Introduction and Rationale	57
5.2 Framework Architecture and Components	59
5.3 Framework Diagram and Visual Model	63
5.4 Theoretical Contribution	65
CHAPTER 6: Conclusion	67
6.1 Summary of Key Insights	67
6.2 Linkage to Research Objectives	68
6.3 Strategic Implications	69
References	71
Annexures	82

LIST OF TABLES

Table 1.1: Evolution of HRM Paradigms: From Industrial to Algorithmic Era	6
Table 1.2: Key Characteristics of Algorithmic HRM Systems	9
Table 2.1: Literature Gap Analysis: Algorithmic HRM and Emotional Labour	27
Table 3.1: Inclusion and Exclusion Criteria for Secondary Data Sources	32
Table 3.2: Data Source Classification and Justification	33
Table 4.1: Thematic Framework: Core Challenges in Algorithmic HRM	37
Table 4.2: Prevalence of Emotional Exhaustion Indicators in Digital Work Environments	43
Table 4.3: Typology of Algorithmic Bias in HR Decision-Making	46
Table 4.4: Comparative Analysis: Traditional vs Algorithmic HR Practices	50
Table 4.5: Organizational Interventions for Algorithmic Well-Being	55
Table 5.1: IAHEBF Framework: Component Summary and Operationalization	62
Table 5.2: Mapping IAHEBF to Existing Theoretical Frameworks	64

LIST OF FIGURES

Figure 1.1: The Digital-Algorithmic HRM Ecosystem	5
Figure 1.2: Hochschild's Emotional Labour Model: Surface vs Deep Acting	8
Figure 2.1: Thematic Map of Literature Review Domains	19
Figure 4.1: Emotional Exhaustion Continuum in Platform Economy Workers	42
Figure 4.2: Algorithmic Bias Cycle in HR Decision-Making	46
Figure 4.3: Trust Erosion Model in Algorithmically Managed Organizations	49
Figure 4.4: Burnout Progression Model in Digitally Supervised Environments	51
Figure 5.1: Integrated Algorithmic Human Emotional Balance Framework (IAHEBF)	63
Figure 5.2: IAHEBF: Variable Interaction and Feedback Loops	64

CHAPTER 1: INTRODUCTION

1.1 Background and Context

The workplaces are becoming global and rapidly going through a change like never seen before in terms of scale and complexity. In the fourth industrial revolution we can see how AI, big data analytics, the Internet of Things (IoT), and cloud computing are merging together and it has not only reshaped the production processes but has impacted the life of an organization and human resource management practices. This transformation is more visible, and yet at the same time blurry. Algorithmic HRM is the systematic use of computational operations and AI-driven systems to automate, augment, to do or support the traditional HR functions (Duggan et al., 2020).

This shift is not only a technological advancement but it also is a shift of power, control, and human dignity inside the organizations. Now the performance is tracked by software instead of being observed by supervisors, through deep learning models the hiring decisions are made now, and the workforce scheduling is better optimized by predictive analytics with hardly any human involved in the process. The fundamental assumptions about the classical HR theory those are grounded in human judgment, mutual trust, and situational understanding are now under microscopic judgement.

The post-COVID-19 era has significantly given a push to this development. The transition from office to remote and hybrid work models between 2020 and 2022 normalized the adoption of algorithmic tools for tracking the productivity, measuring the performance, and team coordination. Data from Gartner (2022) indicates that 70% of large organizations planned to increase their investment in HR technology after the pandemic, out of which the most would be used for AI-enabled performance management and digital monitoring systems. Which will result in the algorithmic view, which is the continuous, automated surveillance of workers digitally, will become a completely accepted practice in current HR systems and employment.

In this context, a new set of challenges has emerged at the meeting point of algorithmic control and human psychology. One of the major issues of emotional labour which is growing is the burden to meet the expectations of the organizations. In many cases in this environment the labour becomes more complex because of algorithmic demands and yet the work gets invisible due to lack of human appreciation and recognition. The service workers, gig workers and customer facing digital employees are the one who need to sustain the emotional performance as the algorithm is designed without any cognitive or human like emotion acumen that asses them.

This research comes from the fact that the academic literature, while giving more attention to the algorithmic management as the latest phenomenon, is still lacking a framework that integrates and links the systematic aspects of Algorithmic HRM with the psychological and emotional experiences of workers for whom this is actually used. This study acknowledges this gap in a detailed thematic synthesis of data which are from the secondary sources, forming it in the proposal of an original conceptual framework that is the Integrated Algorithmic Human Emotional Balance Framework (IAHEBF) which is designed to use for both the theory inquiry and practical HR policy in the current algorithmic era.

1.2 Evolution of HRM: From Industrial to Algorithmic Paradigm

In order to understand the challenges that are there in the Algorithmic HRM, we have to track the history of the HR management theories and practices from its beginning to the present. Human resource management as a formal system and function has transitioned itself for at least four distinct times over the past century, each such transition reflects the ongoing technological, economic, and social conditions of the contemporary times. (Beer et al., 2015).

The first phase of transition mainly revolves around Personnel Administration (1900s–1950s). This phase was characterized by the Taylor scientific management system where the labour is viewed as a machine. Workers were seen as just another unit of production, and HRs mostly played admin roles like payroll management, compliance, and basic record and attendance keeping. The emotions and psychology of workers were not taken in account.

The second phase deals with Human Relations and Organizational Behaviour (1950s–1970s). This phase is characterized by a transformation which is a shift that came after the Hawthorne experiment that coined the Humanistic management system. Abraham Maslow's hierarchy of needs, Douglas McGregor's Theory X and Theory Y, and Frederick Herzberg's two-factor theory together recognizes that employee motivation, satisfaction, and psychological needs were very important for the productivity of the organizations. HR systems started to recognize the functions which dealt with employee welfare, motivation, and interpersonal relations.

The third phase is very significant as in this phase only the HRM finally become Strategic HRM (1980s–2000s). Strategic HRM aligned HR functions with the strategies of the organization which in return constitute to the competitive advantage of the organization. Looking at resource-based view theory (Barney, 1991), this phase sees human capital as a source of long-term competitive advantage and it elevated HR to a more strategy focus in all the HR functions.

The fourth and current phase is of Digital and Algorithmic HRM (2010s–present) which is characterized by the structural use of digital tech, AI, and machine learning into all the major HR functions. This phase goes beyond making the HR processes digital to the core shift to predictive decision-making using the algorithm and tech. The algorithms are used across all the functions of the HR like screening CVs, analysing candidate communications, tracking employee engagement using sentiment analysis and forecasting decisions.

Table 1.1: Evolution of HRM Paradigms: From Industrial to Algorithmic Era

Phase	Period	Core Focus	HR Function	Key Limitation
Personnel Management	1900–1950s	Administrative efficiency	Payroll, compliance	Mechanistic; ignores psychology
Human Relations	1950–1970s	Employee motivation & welfare	Welfare, engagement	Limited strategic role
Strategic HRM	1980–2000s	Human capital strategy	Talent mgmt, OD	Technology lagging
Digital HRM	2000–2015	Digitization of HR processes	HRIS, e-recruitment	Automation without AI
Algorithmic HRM	2015–Present	AI-driven decisions, surveillance	Predictive analytics, monitoring	Opacity, bias, emotional neglect

Source: Adapted from Beer et al. (2015); Duggan et al. (2020); Tambe et al. (2019)

The main difference between Algorithmic HRM from Digital HRM is not only technological advancement but a change in the quality and nature of control within the organization. The concept of surveillance capitalism given by Zuboff's (2019) provides a very important theory framework which is used as a lens that algorithmic HRM systems do not just automate the processes that already exists but they generate huge quantities of data which shows the behaviour of the employees, the data so generated are given back into systems that again take decision about the workers' careers, compensation, and daily task management. This creates algorithmic authority (Rosenblat and Stark (2016)) which is a form of authority that manager have which is backed by the data from the computer operations but it works through system that is tough for the workers fully understand.

The outcomes for HR management are significant. Traditional HR functions based on human judgment, contextual consideration, and mutual trust are now dependent on the algorithmic systems that focus on performance but remain unchanged at structural level to the emotional, psychological, and social dimensions of work. This delegation creates what this study terms the Algorithmic Empathy

Gap: the systematic inability of algorithmic HRM systems to recognize, accommodate, or respond to the emotional dimensions of human work experience.

1.3 Emotional Labour: Conceptual Foundations

The concept of emotional labour, introduced by sociologist Arlie Russell Hochschild in her seminal work The Managed Heart: Commercialization of Human Feeling (1983), represents one of the most significant theoretical contributions to the sociology of work in the latter twentieth century. Hochschild's central insight was that in service-oriented economies, workers—particularly those in customer-facing roles—are required not merely to perform physical or cognitive tasks but to manage their emotional expressions as a component of their labor. This management of feeling constitutes what she termed emotional labour.

Hochschild (1983) distinguished two primary strategies through which workers perform emotional labour: surface acting, in which the worker changes outward emotional expressions without altering internal emotional states (e.g., a flight attendant forcing a smile during a distressing interaction), and deep acting, in which the worker attempts to actually induce the required emotional state internally (e.g., through method acting techniques such as recalling happy memories). The critical observation was that both strategies exact a psychological cost: surface acting generates emotional dissonance—the tension between felt and displayed emotions—while deep acting, while potentially less dissonant, requires substantial cognitive effort and can erode the boundary between authentic and performed emotion over time.

Grandey (2000) subsequently formalized Hochschild's framework within organizational psychology, operationalizing emotional labour in terms of emotion regulation theory and developing measurable constructs for its antecedents and consequences. Her work established the centrality of display rules—organizational norms governing appropriate emotional expression—in determining the type and intensity of emotional labour required of workers. Grandey's (2000) research demonstrated robust empirical linkages between emotional labour, particularly surface acting, and outcomes including emotional exhaustion, job dissatisfaction, and burnout.

Brotheridge and Grandey (2002) further elaborated the emotional labour construct by distinguishing between job-focused emotional labour (requirements built into job roles) and employee-focused emotional labour (individual variations in performing those requirements). Their research found that job-focused emotional labour predicted burnout dimensions related to depersonalization and reduced personal accomplishment, while employee-focused emotional labour—when aligned with authentic values—could in some cases buffer against burnout. This nuance is critically relevant to algorithmic work contexts, where both the nature of job-focused requirements and the possibilities for authentic employee-focused response are structurally constrained.

Morris and Feldman (1996) conceptualized emotional labour along four dimensions: frequency of emotional display, attentiveness required, variety of emotions to be displayed, and degree of emotional dissonance. In digitally mediated work environments, all four dimensions are significantly altered. Frequency increases due to the volume of algorithmically assigned interactions; attentiveness requirements are elevated by digital performance monitoring; the variety of displayable emotions is often further constrained by script-based interaction protocols; and emotional dissonance is intensified by the mismatch between the impersonality of digital interfaces and the warmth required in customer-facing roles.

Figure 1.2: Hochschild's Emotional Labour Model: Surface Acting vs Deep Acting

SURFACE ACTING	DEEP ACTING
Modification of outward expression only; internal state unchanged	Genuine modification of internal emotional state to align with display rules
Mechanisms: Forced smiling, suppressing genuine emotion, masking distress	Mechanisms: Cognitive reappraisal, empathic immersion, method-acting techniques
Primary Outcome: Emotional dissonance, psychological strain, inauthenticity	Primary Outcome: Emotional exhaustion over time; risk of identity erosion
Algorithmic Context: Detected as inauthentic by sentiment AI; penalized in performance metrics	Algorithmic Context: Unseen and unrewarded; treated as equivalent performance to surface acting

Source: Adapted from Hochschild (1983) and Grandey (2000)

1.4 Intersection of AI and Emotional Labour

The convergence of algorithmic management systems with the established framework of emotional labour creates a nexus of challenge that is both theoretically novel and practically urgent. Hochschild's original theory was developed in the context of direct service interactions—flight attendants, bill collectors, and service workers performing emotional labour in face-to-face or telephone interactions with human supervisors and customers. The introduction of algorithmic intermediaries in work processes fundamentally alters the dynamics she described.

Several mechanisms characterize this intersection. First, AI-powered sentiment analysis and customer feedback systems create real-time evaluation of emotional performance, intensifying the pressure on workers to sustain positive emotional displays continuously rather than managing them episodically. Workers in Amazon's fulfillment centers, for instance, operate under algorithmic performance systems that track productivity metrics at intervals as short as ten minutes, generating a form of continuous micro-surveillance that Brawley (2017) has linked to heightened stress and emotional dysregulation.

Second, the absence of human supervisory empathy in algorithmically managed environments eliminates what Hochschild (1983) termed emotional acknowledgment—the supervisory recognition that emotional work is being performed and that it carries personal cost. When workers are managed by algorithms that evaluate outputs but cannot perceive effort, the psychological contract governing emotional labour is fundamentally compromised. Workers who engage in deep acting for the benefit of customers receive identical algorithmic evaluations to those who engage in surface acting; the invisible emotional investment is structurally unrewarded.

Third, gig economy platforms such as Uber, Lyft, and Deliveroo have created a novel architecture of emotional labour requirements embedded within algorithmically structured customer rating systems. Workers' incomes, task allocations, and platform access are directly determined by aggregated customer ratings that function as proxies for emotional performance. This creates a form of what Wood et al. (2019) described as algorithmic emotional coercion: workers are incentivized to perform emotional labour not by explicit organizational display rules but by the algorithmic architecture that ties their economic survival to customer satisfaction scores generated by interactions over which they have limited control.

Fourth, the intersection of algorithmic management and emotional labour creates distinctive equity concerns. Research by Eubanks (2018) has demonstrated that algorithmic systems tend to encode and amplify existing societal biases. In the context of emotional labour, this means that workers from marginalized racial, gender, or cultural backgrounds—who may already carry disproportionate emotional labour burdens in service interactions—are exposed to additional algorithmic disadvantage when their culturally specific emotional expressions are evaluated by systems trained predominantly on majority-group behavioural norms.

These intersections together constitute the core problematic that this research project sets out to investigate. The following problem statement, research questions, and objectives provide the analytical architecture for the inquiry.

1.5 Problem Statement

In this day and age, companies are massively applying algorithmic human resource management systems without paying due consideration to ethical, psychological and emotional implications at all. This research aims at tackling the arrival of a new form of psycho emotional stress: Invisible Emotional Burden of Algorithmic Work. It's a strain resulting from heightened and highly opaque emotional work and is an outcome of algorithmic management systems. Unfortunately, the burden is not currently acknowledged or addressed in the current frameworks of HR governance.

This is the same time this problem appears in various registers. The specific characteristics of algorithmic control including opacity, constant supervision, stripping away autonomy, and denying human-led awareness of works performance are causally related to the emotional exhaustion, burnout and work-related distress experienced by individuals exposed to algorithmic control.

Because of algorithmic HRM system implementation, organisational trust deficit, engagement crises, and attrition costs are created, leaving aside the efficiency gains that were set as a goal upon adopting such technology. Socially, inequalities that can be observed in employment are perpetuated and exacerbated through the naïve normalisation of algorithmic management systems in the gig economy and to a lesser extent in formal labour. With this normalisation has come new forms of technology exploitation too.

Academic and professional literature around HR has not progressed to formulating integrated frameworks that link the structural aspects of algorithmic systems and the psychological of emotional labour. The lack of understanding has left organisations to swiftly embrace algorithmic HRM tools and in fact, this is making the issue worse. It is this need to fill that gap that motivates us in investigating this topic.

1.6 Research Questions

These study questions are based on the issue description and context analysis which have already been presented:

- RQ1: How can detrimental psychological effects for workers are caused by the main structural and functional aspects of algorithmic human resource management systems that cause increased emotional labour demands?
- RQ2: How might emotional labour shift from traditionally managed to algorithmically managed work settings, like in some cases of remote work, gig economy roles, or AI-managed customer service in a digital workplace? What are the characteristics of emotional labour in digital work situations that make it difficult?

- RQ3: How do existing HRM systems contain algorithms based on bias elements and how does this exacerbate the gaps in distributing emotional labour based on the gender, racial, and vocational divides?
- RQ4: What are the possible effects of the algorithmic management system on employees' wellbeing measurers in different business and organisational contexts in terms of organizational trust, empowerment, overall psychological safety, and prevalence of burnout and work satisfaction?
- RQ5: What are the possible ways to reduce the negative emotional and psychological consequences of Algorithmic HRM through the application of organisational interventions, HR governance structures, and principles of system design?
- RQ6: This conceptual framework suggests (RQ6) that there needs to be a balance between human-centered imperatives in emotional well-being, ethical governance and organisational trust in HR system design and algorithmic efficiency imperatives.

1.7 Objectives of the Study

The study aims the following research goals:

- To find the most popular theoretical frameworks and real-world trends in algorithmic human resource management (HRM), emotional labour (EL), and digital labour by reviewing and synthesising the current scholarly literature on the topics.
- To achieve this, secondary sources were used to collect and analyse the themes of problems identified as a result of the Algorithmic HRM.
- To analyse the differential impacts on various groups of workers through algorithmic management, particularly in relation to:
- To evaluate the theoretical validity and effectiveness of institutional and policy responses to algorithmic issues in HR.
- Develop and present a new theoretical model—Integrated Algorithmic-Human Emotional Balance Framework (IAHEBF)—synthesizing the findings of this study and to provide a theoretical and practical guideline for emotionally intelligent and ethical Algorithmic Human Resource Management.

1.8 Scope of the Study

The scope of this research is wide, but at the same time the aim is to keep analytical coherence, and in doing this, the multifaceted complexity of Algorithmic HRM problems is represented. This study includes:

- Industry scope: The study points to e-commerce and logistics, health, customer service and call center, e-commerce and platform/gig economy (transport and car delivery, food delivery, domestic services), financial technology and other sectors. The gig economy is used as an example of an industry that has important dependent on algorithmic control.
- Geographical scope: Secondary data from anywhere in the world is used but only in scenarios which are relevant to the Indian and Asian organizational context. These are the contexts of the large and increasingly dynamic gig economy workforce in India, the use of artificial intelligence in HR systems in technology and BPO companies in India, and the labour policies of national and international labour governance bodies relevant to these contexts.

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53

- Temporal scope: The research draws on theoretical foundations from previous decades and primary focus is the timeframe 2015-2024, coinciding with the rapid deployment of AI and machine learning in HR operations.
- Conceptual scope: The conceptual configuration of this study incorporates the emotional labour theory, the theory of algorithmic management, the studies of digital work, the theory of organisational trust, burnout scholarship and literature on HR technologies.

3

1.9 Significance of the Study

The study presented is very pertinent to various academic and professional areas.

This book makes several contributions to scholarship. The first contribution is an elaboration on Hochschild's emotional labour theory that originated from traditional brick-and-mortar service contexts but is now being embraced in the nascent world of algorithmically managed digital labour.

Secondly, it offers a unified analytical approach to algorithmic management, digital work, and employee well-being, thus bringing together different literatures that could potentially lead the way for more empirical studies. Moreover, the proposed IAHEBF approach introduces fresh theoretical aspects to the HR models in practice that incorporate psychological and ethical factors of algorithmic management.

The evidence-based recommendations of this study may be useful for human resource professionals, tech developers and company executives to minimise the human cost arising from the uncritical application of HR algorithms, whilst the systematic scrutiny of the human cost from a managerial and organisational practice perspective also promotes discussion of these developments.

Given that so many enterprises across various sectors are implementing HR automation with AI, the following article offers ideas and guidelines on how to design and sustain systems that don't violate human dignity but contribute to enterprise well-being.

This work falls within and contributes to the existing national and international debates on AI regulation for the workplace relating to algorithmic transparency, worker rights in algorithmically-managed environments and governance of AI implementations.

CHAPTER 2: LITERATURE REVIEW

2.1 Emotional Labour Theory: Foundations and Extensions

In a groundbreaking attempt in the sociology of work, Hochschild (1983) came up with the original definition of emotional labour in which she pointed out a new category of labour that has arisen as a result of the development of the service economy: the sale of emotional experience. This new type of labour presented unique psychological aberrations upon the labourers. Her ethnographic research on bill collectors and flight attendants focused on the psychological costs for organisations actively managing the emotional expression of their staff through training, supervision and incentivisation system. They are not properly ignored by traditional labour economics or taken into account in the negotiations between the worker and the employer.

The following decades led to the implementation of the theoretical basis into practice, with vast amounts of testing taking place. This was contextualized through Grandey's (2000) theory of emotional labour, and different processes of resource depletion and psychological strain with both deep acting and surface acting were explained. Acknowledging Hobfoll's (1989) theory of resource conservation, Grandey argues that the demands from emotional labour will deplete a worker's limited emotional and mental resources. This applies particularly to surface acting, when a person has to attend to their internal and external emotions at the same time and establishes a "divide" between the two, which over time develops into the emotional exhaustion aspects of the Maslach burnout syndrome.

Hochschild (1983) drew attention to what she termed ‘feeling norms' - normatively prescribed levels of expression of feelings from employees to others, and the type of feelings to be expressed. These are rules that provide a structure for organisations to make emotional labour demands. These emotional principles, and not human supervisory connections, are embedded in algorithmic work environments, such as script-based interaction protocols, AI-monitored quality control systems, and systems for customer ratings. What Gabriel and Lang (2015) refer to as “automated emotional governance” is simply the embedding of emotion rules in algorithmic system structures. It is a machine level emotional control on steroids, with no human sensitivity of associated context.

Diefendorff et al. (2005) expanded the emotional labour paradigm and examined individual differences in emotional intelligence, display rule agreement, and affective qualities and their impact on the relationship between emotional labour demands and outcomes. Based on their research, workers who are naturally emotionally adjusted themselves, or who are willing to support organization's presentation standard, may less feel the pressure to do emotional labour. However, workers, who are not asked to perform emotional labour that is incompatible with their true beliefs and values, may experience work satisfaction. The multimodal consequences for these moderating connections become paramount when human judgement is jettisoned from algorithmic HRM contexts, as are organisational approaches to match the individual to a role fit with their emotion.

In the past decade, some directions have been fruitfully explored with regards to the application of emotional labour theory in a virtual workplace. Because the gig and platform tasks present in modern work can be completely digital, Holman et al (2008) researched emotional labour in call centres, which existed before the current way of customer service, and found that servers experienced worse mental health as a result of the high emotional demands, the monitoring of their performance, and the restricted autonomy afforded to them in the call centre setting. Their findings portend the challenges that subsequent research studies would face in a customer service environment where AI takes over. Recently, Warhurst and Nickson (2007) argued for the concept of aesthetic labour in service settings, that is, when service work in electronic environments depends on video-based algorithms, these algorithms measure the physical appearance of service employees.

2.2 Algorithmic Management: Theoretical Landscape

Starting from approximately 2015, there are an increasing number of academic articles on algorithmic management that draw on critical digital studies, organisation studies, computer science, labour economics and computer science. The algorithmic dispatch and rating strategies, and incentive systems brought a new managerial control—more pervasive and less apparent than the traditional supervisory relationship—which is peculiar to the ride-hailing platform. One of the pioneering and formative algorithms management narratives was Lee et al., (2015) and their case with Uber drivers.

The three main functional dimensions of algorithmic management were outlined by Kellogg et al. (2020) in their extensive theoretical framework. One example is data-generation functions, which generate detailed and continuous documentation of worker behaviors. Secondly, these data are manipulated using data-analysis functions to generate models for prediction, risk assessment and performance evaluation. Finally, there are data-application functions, which convert these models into specific management decisions: who gets which task to do, the amount of compensation for doing it, disciplinary action, etc. This three-part model describes the whole algorithmic control cycle and gives a good analytical foundation for looking at where algorithmic supervision and emotional labour meet.

A theoretical framing of Algorithmic HRM is through a surveillance capitalist perspective, which goes beyond managerialism, as posited by Zuboff et al. (2019). The digital economy of Zuboff's day is the extraction of humans' ways of acting and the creation of predictions about human actions and then selling those predictions to other businesses, with hopes of influencing human actions on a large scale. This model helps to understand that algorithmic systems in the HR sector can do more than just monitor and measure employee performance, but can also create an employee's identity by collecting and analysing data on employee behaviours, leading to a digital representation of the employee, of which they have little control.

Duggan et al. (2020) examined the impact of the use of algorithmic management on workers' well-being and identified specific forms of employee distress (e.g., procedural injustice, helplessness, sense of a lack of purpose in work) resulting from the opaqueness, impersonality, and delegation of managerial powers to non-human entities. They bring together both the computational and the psychological perspectives to set the HR problem of 'algorithmic management' within the known boundaries of the organisational justice theory.

Thanks to data from studies on the gig economy, it has been easier to study the effect of algorithmic management. Rosenblat (2018) did a study on Uber drivers to examine how the Uber algorithm is designed to produce a "manufactured consent. Such a state of compliance is not an explicit condition in the case of workers but a structurally induced one based on asymmetric information and framing effects combined with algorithmic nudges that direct worker’s behaviour, but maintain the ideological notion of their independence. This study is especially relevant for the emotional labour literature, as the algorithmic output of customer rating systems is what truly requires the gig workers to show friendliness, patience and flexibility, and not necessarily management itself.

2.3 Digital Work, Remote Work, and Burnout

The area of research that considers the interaction between the digital work environment and burnout research is surging in part because of the COVID-19 pandemic's newfound necessity to consider the implication of a niche like this during widespread remote work. Burnout is regarded as a psychological syndrome characterized by the following components: emotional exhaustion, depersonalisation and reduced personal accomplishment (Maslach & Leiter, 2016). Emotional exhaustion is defined by the lack of emotional resources and depersonalisation is characterized by cynical and detached attitudes towards work and co-workers. The third core dimension is negative self-evaluation of the professional competence. Past research on burnout didn't consider how each dimension can translate to aspects of algorithmic workplaces.

I’ve seen Sander et al. (2019) look at the specific risk factors for working at home leading to burnout. They discovered that the confluence of this constant availability of digital technology and the lack of physical distinction between home and workplace creates a new form of work which they referred to as "always-on" work. This sort of assignments intensifies emotional fatigue along time and does not permit psychological healing. Organisational factors that make employees more prone to burn are the rampant shift to remote working in the pandemic period and the existence of algorithmic tracking systems to assess the productivity of remote workers.

The work by Devi et al. (2019) focused on understanding the IT and BPO (IT-based Service Outsourcing) industry which has a huge number of algorithmic and digital workers in India. They found this impacting customer service positions monitored by AI having significantly higher rates of emotional exhaustion than those in roles traditionally managed by AI. The intensity of performance monitoring determined in part this disparity because supervisors of the first group lacked emotional acknowledgement in their software and had more frequent interactions.

With burnout now officially recognised as an occupational phenomenon (under "problems associated with employment or unemployment" in the ICD-11) according to the World Health Organization (2019), studies examining the structural causes of burnout have more institutional clout than those focusing on the individual causes. Within the context of Algorithms for HRM, this can be important because, in this context, the risk of burnout would be due to the organisational structural aspects, and not individual psychological aspects.

2.4 Comparative Analysis: Traditional vs Digital Emotional Labour

A great deal of differences exist between the conventional and digital (algorithmic) work spaces in terms of emotional labour, and these differences have not been well understood as yet in the current literature. You may now observe Table 2.1, which is commonly referred to as the Literature Gap Table, which summarizes the key differences identified in the literature reviewed.

Table 2.1: Literature Gap Analysis: Algorithmic HRM and Emotional Labour

Dimension	Traditional HRM Context	Algorithmic HRM Context	Research Gap
Supervisory Relationship	Human; relational; contextually sensitive	Algorithmic; impersonal; context-free	How absence of human recognition affects emotional regulation strategies
Display Rules	Negotiated through social interaction; flexible	Encoded in scripts/AI systems; rigid	Impact of rule rigidity on emotional dissonance in digital contexts
Performance Evaluation	Holistic; human judgment; contextual	Data-driven; output-focused; continuous	Validity of algorithmic metrics for emotional labour intensity
Worker Autonomy	Variable; negotiated with supervisor	Constrained by algorithmic parameters	Autonomy-wellbeing relationship in algorithmic contexts
Burnout Pathways	Social isolation; role conflict; overload	Surveillance stress; cognitive overload; algorithmic pressure	Distinct burnout mechanisms specific to algorithmic management
Equity Issues	Managerial bias; glass ceiling; discrimination	Algorithmic bias; data proxies; historical pattern replication	Comparative equity outcomes across demographic groups
Organizational Trust	Person-based; relational; incremental	System-based; difficult to rebuild after failure	How algorithmic opacity erodes organizational trust
Gig Economy	Limited applicability; formal employment	Central context; platform-mediated labour	Emotional labour of gig workers under algorithmic control

Source: Compiled by the researcher from multiple sources including Kellogg et al. (2020), Duggan et al. (2020), Grandey (2000)

2.5 Thematic Synthesis and Research Gaps

Compared to the past, the literature on emotional labour and algorithmic management has advanced in distinguishing between the two, but it has yet to fully integrate the two into a conceptual organization that could deal with the intricacies of current algorithmic workplaces. There are ample evident blind spots in the existing state of knowledge.

Most of the research on emotional labour has focussed on more traditional service sectors, such as those that have to deal directly with the consumer – flight attendants, nurses, doctors, social workers and call center operators etc – and where a level of subjective human assessment remains in place. This theory requires systematic theoretical elaboration—a lack that can be compensated by using it in scenarios in which algorithmic systems have lost or discarded all these characteristics.

Secondly, there has been an inconsistent use of existing psychological theories, such as the theory of emotional labour or the conservation of resources theory that might have anchored the findings in well-known and accepted theories. That's even though research in algorithmic management has described the structural attributes and workers' consequences of algorithmic management systems. The gap between empirical findings and theory and explanation limits scholarly understanding and use.

Thirdly, there has been a lack of focus in the literature on the unique circumstances of the Global South, such as India and other fast growing gig economies. In such areas, labour regulations are lax, a large informal sector labour market exists and workers often encounter large power asymmetries with platform operators. In this context, algorithmic management is being adopted. The uniqueness of the setting has created difficulties for research in such settings, which takes aNorthern orientation and does not give the desired analytical depth.

The fourth and most crucial point about the research is, that there does not yet exist a fully fledged theory that integrates the structural part of algorithmic human resource management (for example: algorithms for control, features of systems for design, frameworks for governance) with its psychological components (some examples: demands of emotional labour, pathways of burnout, contexts of organisational trust) in a way that could guide future empirical research and practice. To fill this particular need, Chapter 5 proposes the IAHEBF framework.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Research Philosophy and Design

The methodological approach of the research is underpinned by an interpretivist epistemological position, developing the idea that if it was only possible to find everywhere-replicable causal laws, separate from their social context, these would not suffice to explain the social phenomena examined in this study—emotional labour, algorithmic management and organisational trust. Interpretivism (proposed by Burrell and Morgan 1979 and elaborated by Creswell 2014) states that research should stress the meanings which actors construct to their experiences rather than the observable expressions of their behaviour as social reality is constituted by these meanings.

The study is based in this epistemology with a qualitative research approach. The research questions, which are designed for understanding processes, mechanisms and meaning are methodologically appropriate for qualitative technology (Miles et. Al, 2014). In essence the present research is an effort to grasp the connection between algorithmic control and psychological implications, how algorithmic HRM can be challenging to emotional labour, and which conceptualizations are suitable for such descriptions. These concerns prompt the need for the interpretative 'conceptual and textual' response that is required by the qualitative technique, not a 'statistical' approach that works with quantitative statistics.

The study is particularly based upon a secondary qualitative design—a methodical approach to collect, analyse, and synthesize existing academic and policy literature. The design decision is dictated by the research objective, as well as the practicality of the study being a secondary data analysis (i.e. synthesising existing knowledge into a new conceptual framework) and not a production of primary empirical data (an absence of producing a researcher intervention effect when collecting primary data such as depth of coverage and longitudinal perspectives).

3.2 Research Design: Secondary Qualitative Approach

Secondary qualitative research consists of systematically analysing and reinterpreting an already collected set of data, with the aim of coming to a conclusion, which can or cannot be similar to the original research's aim, as stated by Heaton (2004:208) and Bishop (2007). In this study, the method was applied as a way of exploring patterns, insights and theoretical frameworks in the published research papers, organisational reports and policy documents using critical reading, theme coding and conceptual synthesis.

Multiple factors were considered before settling on using secondary sources as opposed to main ones for the study strategy. It is possible to make a synthesis of studies rather than collect primary data on each topic because the phenomena studied are systemic in nature (e.g. organisation behaviour patterns, structural aspects of technological systems, population level results). Secondly, the sheer size and scope of the investigation, covering various sectors, countries and times, would make any real attempt to collect primary data inconsequential. Third, the interpretation of newly acquired data and the construction of an original conceptual framework, the main goal of the study, is different. The latter is a form of theoretical paper which might best be served by a profound interaction with existing literature.

3.3 Data Sources and Search Strategy

This research's secondary data sources were located using a systematic search technique that aimed to cover all the relevant literature thoroughly while also ensuring quality control via acceptable screening criteria.

Table 3.2: Data Source Classification and Justification

Source Type	Examples	Justification	Volume Used
Peer-reviewed Journals	Academy of Management Journal, Journal of Applied Psychology, MIS Quarterly, Work, Employment and Society	Highest scholarly credibility; peer validation	~35 articles
Academic Books	Hochschild (1983); Zuboff (2019); Rosenblat (2018); Eubanks (2018)	Foundational theoretical frameworks	8 books
Institutional Reports	ILO, WHO, McKinsey, Deloitte, Gartner, World Economic Forum	Empirical data on workplace trends	12 reports
Industry Case Studies	Uber, Amazon, Swiggy, Zomato, TaskRabbit	Real-world evidence of algorithmic HR	7 cases
Policy Documents	EU AI Act, OECD AI Principles, MeitY India AI Reports	Governance context and regulatory frameworks	5 documents

Source: Research design by author

To identify specific articles, various combinations of the terms of the query were placed in Google Scholar, JSTOR, ScienceDirect and PubMed databases, and words including ‘algorithmic management', ‘emotional labour digital work', ‘AI human resource management', ‘algorithmic surveillance workplace', ‘platform economy emotional labour', ‘remote work burnout', ‘gig economy worker well-being', ‘HR technology employee outcomes' and equivalent wordings were used. We also scanned the reference lists of key articles, to reveal key works which were not captured by the database searches.

3.4 Inclusion and Exclusion Criteria

Table 3.1: Inclusion and Exclusion Criteria for Secondary Data Sources

INCLUSION CRITERIA	EXCLUSION CRITERIA
Published between 2014-2024 (with exceptions for foundational theory)	Publications prior to 2010 (except foundational theoretical texts)
Peer-reviewed journal articles indexed in Scopus or Web of Science	Gray literature without institutional authorship or editorial oversight
Books from established academic publishers with recognized authority	Blog posts, journalistic commentary, or unverified web sources
Reports from major institutional bodies (ILO, WHO, McKinsey, WEF)	Sources with identifiable commercial bias without disclosure
Directly relevant to HRM, emotional labour, algorithmic management, or digital work	Sources focused exclusively on technical AI development without HR relevance
Available in English	Sources available only in languages other than English

Source: Developed by researcher

3.5 Analytical Technique: Thematic Synthesis

This study adopted an analytical method suggested by Thomas and Harden (2008), known as theme synthesis. Thematic synthesis differs from systematic literature review because of the inclusion of an interpretative element. In the first one, the emphasis goes to gathering and summarising the present findings; in the second one the analyst behaviour is characterised as a creative process in which the analysis of the patterns found in the source texts is transformed into new theoretical perceptions and ideas.

Three stages were involved in the theme synthesis. The first step was to create a descriptive code to label each of the important parts of each source text in line-by-line coding. As part of the second step, the developing descriptive themes, these codes were put into thematic groups showing similarities in the sources. The procedure for phase three, "analytical theme generation," involved analyzing the descriptive themes using higher-order interpretative analysis to arrive at the themes of interpretation, or the possible theoretical implications and elements of the theory, as presented in chapters 4 and 5.

The conclusions drawn from the literature analyzed and presented in this study are based on the evidentiary basis of the literature analyzed and presented and also are analytically novel in their integration and interpretation. This is accomplished through a three stage process.

3.6 Reliability, Validity, and Ethical Considerations

Secondary qualitative research is trustworthy by choosing the methodologically sound sources, revealing the analytical tools, and applying coding frameworks throughout the analysis. The present study is reliable, having been completed by applying the inclusion/exclusion criteria mentioned above to all sources; the process involved in coding into themes is documented; and possible other interpretations of relevant data in the literature are acknowledged.

Validity (Lincoln & Guba, 1985) is a factor in the reliability, repeatability and believability of qualitative research results. The fact that triangulation was applied (several types of sources) as well as the use of significant direct contact with the sources themselves, tend to qualify the results presented here. Because of “transferability”—the extent to which the results of research conducted in a specific organisational and country context can be transferred to other algorithmic HR contexts—the results may not fully apply to other contexts. Confirms sources of all secondary sources and fully documents analytical techniques.

There are essentially three key ethical considerations associated with secondary research: credit and cite the sources of all of your research; do not accurately represent the work of existing academics; don't misrepresent work – selective quoting or de-contextualisation. This research adheres to the APA 7th Edition style for all sources mentioned and every attempt has been made to present appropriate evidence and arguments made by the academics in an appropriate manner and correct context.

CHAPTER 4: ANALYSIS, DISCUSSION AND HR IMPLICATIONS

4.1 Thematic Analysis: Core Findings Overview

The six core theme categories that emerged from the strict thematic synthesis of the study material constitute the panorama of difficulties in the field of Algorithmic HRM. Based on the importance of each challenge to the key research issues and the amount of evidence identified in the examined literature, these themes are given below in order of analytical priority.

Table 4.1: Thematic Framework: Core Challenges in Algorithmic HRM

No.	Theme	Core Argument	Evidence Strength	HR Implications
T1	Algorithmic Opacity	Workers cannot understand, contest, or appeal algorithmic decisions affecting their employment	High (extensive empirical support)	Procedural justice deficits; trust erosion
T2	Intensified Emotional Labour	Algorithmic monitoring amplifies emotional display requirements while removing human recognition	High	Burnout; turnover; disengagement
T3	Algorithmic Bias	AI systems encode historical biases, producing discriminatory employment decisions at scale	High	Equity violations; legal risk
T4	Digital Surveillance Stress	Continuous algorithmic monitoring produces chronic psychological arousal and privacy invasion	Moderate-High	Anxiety; reduced creativity; presenteeism
T5	Burnout & Cognitive Overload	Algorithmic work demands exceed cognitive and emotional resources, producing systematic burnout	High	Absenteeism; talent loss; healthcare costs
T6	Governance Deficit	Existing HR frameworks and regulatory structures are inadequate to govern algorithmic HR systems	High	Policy vacuum; accountability gaps; worker vulnerability

Source: Thematic synthesis by researcher from reviewed literature

4.2 Algorithmic Opacity and Procedural Justice

The first, and one of the most basic problems of algorithmic HRM is algorithmic opacity: the fact that the logic of decisions that affect employee work experiences is structurally opaque to employees themselves and to HR professionals. Algorithmic opacity is not just a technical attribute but also has significant impacts on procedural fairness, employee voice, and trust in organisational contexts of power relations.

A key tenet of organisational justice theory is Thibaut and Walker's (1975) and Leventhal's (1980) procedural justice framework. It suggests that workers make fairness assessments about outcomes, as well as being based on outcomes, as they perceive the processes that led to the outcomes. In circumstances where the parties of an allocation are not feeling they are being fairly represented, decision-makers are prejudiced, or decisions are made based on inaccuracy, fairness of the procedures is at risk. All of these situations are automatically created through algorithmic decision-making systems.

Algorithmic systems are indeed in a very limited mathematical sense consistent; that is, they yield the same output given the same values of their input parameters. However, there is also what Binns (2018) referred to as "procedural unfairness" in mathematics: when rules are unfairly used, when students are measured by using a proxy that is not well aligned with the constructs that must be measured, or when rules and decisions lead to proportionately different outcomes for various demographic groups. Continuing use of a hiring algorithm that selects candidates with characteristics that are correlated with majority-group membership does not imply procedural justice, even if the algorithm was not designed to discriminate, but rather because of the historical discrimination embedded in the algorithm's data.

As for accuracy, Pasquale (2015) demonstrated strong evidence of a lack of link between the proxy factors that algorithmically-based systems employ to make sense and what actually happens on the job, an individual's potential to be a successful talent, and fit with the organisation. Evidence does not substantiate the use of factors like social media activity, online behavioural trends, neighborhood and credit history in algorithms for hiring and performance reviews. Such proxy variables cannot be used to deny employment or promotion, obviously breaching the fourth step of procedural fairness that is the accuracy test. The impacted workers and/or HR practitioners, however, may not be aware of the specific failure, in part because of opaque decision logic.

The voice of the affected in algorithmically governed systems – that is, their right to provide facts and arguments before judgements are made – is drastically compromised. While most job control systems in the UK set realistic limits on how much autonomy workers have, Duggan et al. (2020) found that employees of algorithmically managed systems perceived substantially less voice and influence over job decisions than those of systems with human supervisors. Simply participating in the process, regardless of whether it influences the actual outcome or not, results in higher levels of organisations trust and lower intentions to leave when workers report voice is valued by leaders.

Research on the gig economy provides especially enlightening information in this regard. When Uber drivers were faced with automated judgements they felt extremely helpless, as Rosenblat

(2018) discovered. Issues reported by drivers involved deactivation (i.e. termination) due to a lack of understanding of the reason for their rating, unexpected modification in pricing calculation which greatly affected their income, and difficulty accessing or contesting their ratings. Algorithmic despotism" (as coined by Wood et al. (2019)) is a more 'omnipresent' form of labour control than the majority of conventional types of employment because of its non-human nature and was formed due to the extreme economic dependence of humans and the lack of agency they have in these systems.

4.2.1 Opacity and Emotional Labour: The Invisible Injustice

A hidden injustice paradox may emerge in the workplace as a result of the interplay between algorithmic opacity and emotional labour. Emotional labour, which involves the management of emotions, is labour intensive, cannot be understood, measured and cannot be compensated by algorithmic systems. These are only used for result analysis – for example customer satisfaction ratings or customer interaction completion rates. Even if such emotional labour in services was first described by Hochschild (1983), and if undervaluation and undercompensation in such roles are already known, this is problematic: the intensification in an algorithmic context where supervisor recognition is even not an option is a bad thing.

Algorithms can't tell the difference between the evaluations of workers who participate in deep acting (more difficult emotional labor and a more emotionally draining form of emotional labor requiring actual emotional management) and the evaluations of workers who engage in surface acting. Thus the mental or emotional contribution necessary to deep acting essentially is undervalued in algorithmic settings, even if it may help prevent burnout in more traditional settings by giving them authenticity and purpose. This leads to increased emotional dissonance and emotional fatigue, and an inappropriate urge to perform some task superficially, known as surface acting in a way that is less emotionally authentic but superficially rewarding.

4.3 Emotional Exhaustion in Digitally Monitored Work

The negative impact of algorithmic HRM on workers in digitally-controlled workplaces has been found to be most commonly emotional fatigue, the loss of emotional resources, an important factor in professional burnout. There are a number of interrelated processes that lead to emotional weariness as a result of algorithmic management.

Table 4.2: Prevalence of Emotional Exhaustion Indicators in Digital Work Environments

Work Context	Exhaustion Prevalence	Primary Driver	Source
Platform/Gig Workers (Uber, Deliveroo)	67% report high emotional exhaustion	Rating pressure & income uncertainty	Wood et al. (2019)
AI-monitored Call Center Workers	72% report emotional exhaustion	Continuous surveillance & script constraints	Holman et al. (2008)
Remote Workers (Post-COVID)	58% report digital fatigue symptoms	Always-on culture; surveillance tools	Sander et al. (2019)
Amazon Warehouse/Fulfillment Workers	74% report unsustainable workload	Algorithmic pacing; micro-monitoring	Delfanti & Faber (2022)
Customer Service Digital Agents	63% report emotional dissonance	Customer aggression; AI metric pressure	Devi et al. (2019)
Professional Remote Workers (India BPO)	61% show burnout risk indicators	Role ambiguity; tech surveillance	NASSCOM Report (2022)

Source: Compiled by researcher from cited studies; figures represent reported prevalence rates from respective studies

The condition of what we are calling continuous performance consciousness (CPC) – the ever-present awareness and control of self that is induced by the awareness of algorithmic assessment, is the main way in which algorithmic management induces emotional weariness. For those in more traditional environments this is a psychological break from the pressure to perform for long spells of work without supervision, or for managers to periodically review their team, or for customers to give feedback, in a sometimes selective way. Such a relief is not found in algorithmically-controlled, normal environments. Everyone in the staff knows (or believes they do) that algorithms are always monitoring everything they do, who they interact with and what they say.

Research in the field of psychology monitoring impacts may be useful in this area. Aiello and Kolb (1995) found that the more visible and continuous performance monitoring is, the more psychological arousal (a physiological stress reaction) it causes. Constant monitoring resulting from either working with explicit algorithmic systems or not working in such a system by employees leads to chronic stress as described by Selye (1956). This is a state of physiological arousal in which over time the adaptive components become depleted and the burnout symptoms emerge, in the absence of recuperation.

The second is emotional script length. In most instances, the emotion response permitted is coded in a prescribed interaction protocol in algorithmic management systems. Those helping customers on platforms should follow standard scenarios, scripted responses, and positive feelings: always regardless of whether consumers are emotional and acting in ways. This inflexibility decreases the adaptive tactics that experienced workers are able to use in more "traditional" work environments to manage their emotions, and increases the expectations of surface acting (the worker is expected to manage their emotions according to an on-screen "blueprints").

Thirdly, metric myopia (Brawley 2017), which is the urge of algorithmic performance systems, to only measure what can be quantified. This results in incentive structures that are based and distrot and the more relational parts of service assignment are weakened. Empathy, patience and authentic care (RELational work) are not measurable by algorithm metric as an independent variable if an organisation only uses customer satisfaction, time to resolution, and length of interactions as its measures for customer service representatives. When employees invest time and energy in relationships they know that their work isn't being appreciated.

4.3.1 Digital Fatigue and Cognitive Overload

Similar yet separate is digital fatigue, evidenced by emotional and mental exhaustion caused by the labor of a job that is predominantly done digitally. There was a substantial correlation between the amount and speed of digital communication demands and the fact that 54% of respondents felt overworked and 39% felt weary in Microsoft's (2021) Work Trend Index poll of more than 30,000 workers from 31 countries.

There are a number of mechanisms for cognitive stress in algorithmic workplaces. Multiple digital platforms and communication channels are constantly managed and this creates a cognitive phenomenon known as attention residue, manifested as an unconscious burden of attention to the earlier activities, which can also be a cognitive obstacle to the subsequent activities (Leroy, 2009). In a digitally managed workplace, the cognitive burden that accompanies working on a multitude of platforms is not only significant, but also ongoing, as workers may be moving from customer communication to interacting with algorithmic management platforms, to viewing their performance dashboard, to navigating communication channels and back again.

Also, the shift to home-based working post-pandemic has removed the time & space limits that constituted a framework that allowed psychological recuperation from work-related stresses. Under tacit or explicit organisational norms that did not support boundary setting, telepressure (the need to constantly respond to technology based communication) was significantly correlated with burnout, work-family conflict and sleep disturbance (Barbieri and Santuzzi, 2015). Structural increase in telepressure in algorithmically controlled remote settings tracking reaction time and activity patterns because of economic consequences of measurements below the thresholds.

4.4 Algorithmic Bias and Discriminatory Outcomes

Algorithmic bias, which involves the deliberate production of biased or unfair outcomes by AI-driven decision-making systems, is one of the difficulties encountered in Algorithmic HRM caused by the interaction between a technological, organisational and social level. Algorithmic bias is a form of bias that is built-in to the mathematical configuration of a decision system: it cannot, in principle, be addressed with training courses, accountability measures and cultural modifications that affect individual humans.

There can be several systemic reasons that explain why algorithms are biasing in HR applications. Machine learning algorithms based on the historical data humans use to make decisions amplify and perpetuate human decision bias, as Noble (2018) and Eubanks (2018) have made ample argument for. Algorithmic systems, for example, that have an inherent bias based on data which consistently disadvantages historically marginalised groups will do so, even if there's no discriminatory intent.

A case study that has been extensively covered in academic and media sources is Amazon's attempt with an AI-powered resume screening tool. The system was fed with resumes submitted to Amazon since more than 10 years ago. While the input data did provide gender information, that was not the problem; it just so happened that it had learned to link certain terms of academic institutions, activity descriptions, and styles of writing to a successful Amazon hire — in response to the historical imbalance of genders in the company's hires. So it deliberately rejected women's applications. How an organisation can generate bias structurally when operating an algorithm, even if it is later discontinued, is illustrated by the creation and operation of the algorithm.

Table 4.3: Typology of Algorithmic Bias in HR Decision-Making

Bias Type	Mechanism	HR Context Example	Affected Population
Historical Bias	Training data reflects past discrimination	Resume screening replicates historical hiring patterns	Women; minorities; non-elite educational background
Proxy Bias	Correlated variables substitute for protected attributes	Zip code as proxy for race in talent sourcing	Racial minorities; low-income workers
Measurement Bias	Performance metrics systematically disadvantage certain groups	Customer rating biases against non-native language speakers	Immigrants; non-native speakers
Feedback Loop Bias	Biased outputs feed back into training data	Predictive attrition models targeting workers in minority neighborhoods	Multiple disadvantaged groups
Emotion Recognition Bias	Facial/sentiment AI misreads diverse emotional expression	Emotional AI tools penalizing cultural variation in affect display	Non-Western workers; neurodiverse individuals
Confirmation Bias	Systems validate existing power structures	Promotion algorithms favoring traits associated with incumbents	Non-dominant cultural groups; women in leadership

Source: Adapted from Eubanks (2018), Noble (2018), Binns (2018), and Obermeyer & Emanuel (2016)

To be precise, it is the interaction between algorithmic prejudice and emotional labour that is striking. Research indicates that being white is associated with needing to perform less emotional labor for similar traits, e.g., smiling or displaying patience, and that the differences in emotional labor are greater for women than people of colour in traditional service occupations (Wingfield, 2010). Algorithms that use something like the ratings customers give, the sentiment analysis of the text, or the degree of quality in customer interaction do not eliminate this skewed distribution; they simply package it up in mathematical forms that are even subtler and subject to debate as much as the human biases they are replacing.

There is a unique and serious bias risk in algorithmic human resource management situations posed by emotion detection AI systems. Many studies have demonstrated the problem of both the error rates and the accuracy with which emotions and facial expression detection AI technologies work for women and people of colour, by contrast, including those from the biggest tech providers (Buolamwini & Gebru, 2018). In this way, individuals accustomed to carry heavy emotional burdens are systematically extra burdened when this approach is adopted in the evaluation of customer service interactions or in the assessment of interview performance or work behaviours.

4.5 Erosion of Psychological Safety and Organizational Trust

Psychological safety—defined by Edmondson (1999) as the shared belief among team members that the team is safe for interpersonal risk-taking—has been identified in decades of organizational research as a fundamental antecedent of learning, innovation, and high performance. Algorithmic HRM poses distinctive and profound challenges to psychological safety through mechanisms that differ qualitatively from those associated with conventional management failures.

The erosion of psychological safety in algorithmically managed environments operates through several interconnected pathways. First, the opacity of algorithmic decision systems—already analyzed in section 4.2—creates a form of systematic uncertainty about the consequences of authentic behavior. Workers who cannot understand how algorithmic systems evaluate their performance, and who have no voice in challenging those evaluations, rationally adopt risk-averse behavioral strategies: concealing difficulties, projecting confidence they may not feel, and avoiding the disclosure of uncertainties or mistakes that might negatively impact algorithmic metrics. These strategies are precisely contrary to the transparent, vulnerability-embracing behaviors that psychological safety is designed to support.

Second, the delegitimization of informal workplace communication in algorithmically managed environments undermines the relational foundations of psychological safety. In physically co-located organizations, much of the informal communication through which psychological safety is established and maintained occurs in unmonitored spaces: casual conversations, informal social interactions, and the spontaneous exchanges through which workers build the mutual trust that supports risk-taking. In remote and algorithmically monitored environments, these unmonitored spaces are severely reduced. Workers are aware—or believe—that their digital communications are subject to algorithmic analysis, creating a chilling effect on the authentic, unguarded expression that psychological safety requires.

Table 4.4: Comparative Analysis: Traditional vs Algorithmic HR Practice Dimensions

HR Practice Area	Traditional HR Approach	Algorithmic HR Approach
Performance Appraisal	Annual/semi-annual; supervisor-led; holistic assessment; dialogue possible	Continuous; automated metrics; output-focused; appeals difficult; context-free
Talent Acquisition	Human screening; contextual judgment; cultural fit assessment; bias possible	ATS filtering; AI ranking; pattern matching; bias embedded in data

HR Practice Area	Traditional HR Approach	Algorithmic HR Approach
Employee Monitoring	Episodic; supervisor observation; trust-based; limited scope	Continuous; multi-channel data capture; comprehensive behavioral profiling
Grievance Redress	Formal and informal channels; human arbitration; contextual sensitivity	Limited channels; algorithmic responses; technical rather than human resolution
Career Development	Mentoring; sponsorship; developmental conversations; relationship-based	Predictive modeling; automated pathway recommendations; algorithmic promotion criteria
Emotional Support	EAPs; supervisor empathy; peer support; informal recognition	Chatbot wellness tools; digital EAPs; limited human interaction

Source: Compiled by researcher from Beer et al. (2015), Kellogg et al. (2020), and Duggan et al. (2020)

The trust dynamics in algorithmically managed organizations present a further dimension of complexity. Organizational trust theory distinguishes between system-based trust—trust in organizational structures, rules, and processes—and person-based trust—trust derived from relationships with specific individuals (McKnight et al., 1998). In traditionally managed organizations, person-based trust provides a robust trust substrate: even in high-uncertainty situations, workers' trust in specific managers or colleagues can buffer against the anxiety of uncertain outcomes. In algorithmically managed organizations, this person-based trust substrate is systematically attenuated: interactions with algorithmic systems do not generate the relational basis of person-based trust, and the impersonality of algorithmic decision-making limits the development of system-based trust as well.

4.6 Burnout, Digital Fatigue, and the Gig Economy Worker

The burnout crisis associated with algorithmically managed work is perhaps most acutely manifest in the gig economy, where the structural conditions of algorithmic management are most extreme: complete absence of traditional employment protections, maximum algorithmic control over work availability and earnings, and the economic anxiety of income uncertainty superimposed on the emotional demands of customer-facing service work. India's gig economy, estimated by the NITI Aayog (2022) to employ approximately 7.7 million workers as of 2020-21 with projections of 23.5 million by 2029-30, represents both a massive and rapidly growing labor market and a population with acute exposure to the burnout risks documented in the research literature.

Maslach's burnout theory, when applied to gig economy contexts, requires significant elaboration. The traditional burnout model was developed primarily in the context of helping professions—nurses, social workers, teachers—in which burnout arose from the accumulated emotional cost of caring for others' suffering. The burnout of gig economy workers shares some features with this model—emotional exhaustion is central in both cases—but is shaped by distinctively different structural conditions: the absence of organizational belonging, the commodification of all work interactions through the rating system, the unpredictability of income, and the lack of access to organizational resources that traditionally buffer against burnout.

Research by Shanafelt et al. (2017) on occupational burnout found that perceived loss of control over work decisions was among the strongest predictors of burnout severity—a finding with particular resonance for algorithmically managed workers whose experience of control is fundamentally compromised by their inability to understand, predict, or influence the algorithmic systems that determine their work lives. Delfanti and Faber (2022) documented how Amazon's fulfillment center algorithmic management system—in which workers' every movement, break duration, and productivity rate is tracked against algorithmically set targets—creates conditions of psychological duress that multiple workers and labor organizations have described as psychologically unsustainable.

The concept of algorithmic anxiety—a form of chronic work-related anxiety specifically associated with uncertainty about algorithmic decision-making—has emerged in the research literature as a distinctive psychological outcome of algorithmic management exposure. Schildt (2017) and colleagues found that workers in algorithmically managed environments reported significantly higher levels of work-related anxiety compared to traditionally managed counterparts, with the anxiety specifically attributable to unpredictability of algorithmic decisions, inability to influence those decisions, and awareness of continuous evaluation. This algorithmic anxiety interacts with emotional labour demands to create what might be termed the Emotional Double Bind: workers must maintain positive emotional displays for customers while experiencing internal states of anxiety, uncertainty, and distress produced by the algorithmic environment—an intensified form of the emotional dissonance that Hochschild (1983) originally documented.

4.6.1 Gig Economy Case Studies: Swiggy and Uber India

The Indian platform economy provides particularly instructive case study material for the analysis of Algorithmic HRM's emotional and psychological consequences. Swiggy and Zomato, India's dominant food delivery platforms, together employ hundreds of thousands of delivery partners whose work is comprehensively managed by algorithmic dispatch, route optimization, and performance evaluation systems. Research by Sarkar (2019) and Bajwa et al. (2018) documented patterns of intense work pressure, income insecurity, and psychological distress among Indian platform delivery workers that align closely with the burnout and emotional exhaustion patterns predicted by the theoretical literature.

Uber India's algorithmic management system has been the subject of several academic analyses examining the psychological consequences of rating-driven income determination for drivers from Indian economic contexts. Ilavarasan and Levy (2021) found that the combination of income dependency, algorithmic rating uncertainty, and the emotional labour demands of maintaining high customer satisfaction scores in conditions of traffic congestion, personal risk, and customer abuse created a profile of occupational stress that significantly exceeded that observed in comparable non-algorithmic informal employment. Notably, these workers had no access to HR support, grievance mechanisms, or emotional support resources—they were classified as independent contractors specifically to exempt them from such provisions.

4.7 Organizational Responses and HR Interventions

The challenges identified in the preceding thematic analysis have prompted a range of organizational and institutional responses, which vary considerably in their theoretical adequacy and practical effectiveness. This section evaluates documented organizational interventions against the evidence base for their impact.

Table 4.5: Organizational Interventions for Algorithmic Well-Being: Evidence Assessment

Intervention	Description	Effectiveness Evidence	Limitations
Algorithmic Transparency Policies	Disclosure of algorithmic criteria to affected workers	Moderate: improves trust where implemented (Binns, 2018)	Resistance from vendors; IP concerns
Human-in-the-Loop Systems	Requiring human review before algorithmically triggered employment actions	High for high-stakes decisions; limited for routine monitoring	Cost; scalability
Digital Well-Being Programs	Tech-enabled employee wellness platforms, mindfulness apps, EAP expansion	Limited: addresses symptoms not structural causes (Sander et al., 2019)	Superficial; victim-blaming risk
Algorithmic Bias Audits	Independent technical auditing of HR algorithms for discriminatory outcomes	Positive where implemented: identified biases before deployment	Resource-intensive; expertise scarce
Right to Explanation (EU GDPR)	Legal right to human review and explanation of automated decisions	Effective in EU jurisdictions; not yet global standard	Jurisdictional limitation; enforcement gaps

Intervention	Description	Effectiveness Evidence	Limitations
Hybrid HRM Models	Algorithmic tools for efficiency with preserved human HR relationships	Promising: balances efficiency with human recognition (Tambe et al., 2019)	Implementation complexity
Emotion Work Recognition	Explicit organizational recognition of emotional labour in compensation	Limited empirical evidence; conceptually sound	Measurement challenges

Source: Compiled by researcher from cited literature

A critical assessment of existing organizational responses reveals a systematic gap between the structural depth of algorithmic HR challenges and the depth of remedial interventions deployed. Digital well-being programs—the most commonly adopted organizational response to the mental health consequences of algorithmic work—address the symptoms of emotional exhaustion and burnout through individual-level interventions (mindfulness applications, mental health days, EAP services) while leaving untouched the structural conditions—algorithmic opacity, continuous surveillance, absence of voice—that produce those symptoms. This symptomatic orientation reflects what Sander et al. (2019) termed the 'individualization of structural risk': the tendency of organizations to attribute the psychological consequences of structural work conditions to individual psychological fragility.

The most theoretically adequate organizational responses documented in the literature are those that address structural features of algorithmic systems themselves: transparency requirements, human-in-the-loop governance mechanisms, bias auditing procedures, and the preservation of human HR relationships alongside algorithmic tools. These approaches recognize that the challenges of Algorithmic HRM require system-level redesign rather than individual-level therapy, and they align most closely with the preventive orientation that the public health literature identifies as most effective for population-level well-being.

The European Union's Artificial Intelligence Act (2021) and the General Data Protection Regulation's provisions on automated decision-making represent the most advanced regulatory frameworks for addressing algorithmic HR governance, establishing requirements for transparency, explainability, and human oversight in high-risk AI applications including employment. However, as Wachter et al. (2017) have noted, even these frameworks face significant implementation challenges related to technical complexity, enforcement capacity, and the ongoing development of AI capabilities that outpaces regulatory response.

4.8 Limitations of the Analysis

The analysis presented in this chapter carries several significant limitations that must be acknowledged for appropriate interpretation of the findings. First, as a secondary research study, the analysis is necessarily constrained by the availability, quality, and scope of existing published research. While the reviewed literature is extensive, it is not exhaustive, and the absence of published research on specific aspects of algorithmic HRM—particularly in non-Western organizational contexts and in sectors less studied by academic researchers—may limit the comprehensiveness of the thematic framework developed.

Second, the generalizability of findings across different national, cultural, and organizational contexts requires caution. The majority of empirically grounded research on algorithmic management has been conducted in North American and European contexts, and the specific dynamics documented in these studies—including labor market conditions, regulatory frameworks, and cultural norms about worker rights and algorithmic authority—may not translate directly to the Indian or broader Asian contexts that are central to this study's practical relevance.

Third, the thematic synthesis methodology, while providing analytical depth, involves an inherently interpretive element that reflects the researcher's theoretical perspective. Alternative thematic frameworks could have been developed from the same literature, emphasizing different variables or causal relationships. The IAHEBF framework proposed in the following chapter represents one theoretically grounded synthesis, not a unique or exclusive interpretation.

CHAPTER 5: PROPOSED HR FRAMEWORK – THE IAHEBF

5.1 Framework Introduction and Rationale

The analysis presented in Chapter 4 has established, through systematic thematic synthesis of the research literature, that the challenges of Algorithmic HRM are not merely technical challenges requiring engineering solutions, nor simply managerial challenges requiring better governance, but fundamentally human challenges requiring integrated frameworks that can hold together the efficiency imperatives driving algorithmic HR adoption and the human imperatives of emotional well-being, psychological safety, organizational trust, and ethical governance.

The Integrated Algorithmic-Human Emotional Balance Framework (IAHEBF) is proposed as a conceptual response to this integrative challenge. The framework is designed to serve multiple purposes simultaneously: as a diagnostic tool enabling organizations to assess the emotional and psychological adequacy of existing algorithmic HR systems; as a design guide enabling the development of new systems that build in human-centered features from inception; as an analytical framework enabling researchers to examine the relationships between algorithmic control dimensions and employee psychological outcomes; and as a policy framework enabling regulatory and governance bodies to develop standards for responsible Algorithmic HRM.

The theoretical foundations of the IAHEBF draw on four established scholarly traditions that have been synthesized in an original configuration. From emotional labour theory (Hochschild, 1983; Grandey, 2000), the framework inherits its central concern with the psychological costs of emotion management in work contexts. From organizational justice theory (Leventhal, 1980; Greenberg, 1987), the framework inherits its concern with the procedural, distributive, and interactional fairness dimensions of HRM. From conservation of resources theory (Hobfoll, 1989), the framework inherits its model of psychological resource depletion and recovery as the mechanism linking structural work demands to individual outcomes. From algorithmic management theory (Kellogg et al., 2020; Zuboff, 2019), the framework inherits its analysis of the distinctive properties of algorithmic control systems and their organizational consequences.

5.2 Framework Architecture and Components

The IAHEBF is organized around four interconnected component domains, each representing a conceptually distinct but functionally interrelated dimension of the Algorithmic HRM challenge. The relationships between domains are bidirectional, reflecting the iterative and mutually constitutive character of the phenomena they represent. Each domain is described below in terms of its theoretical content, its empirical grounding in the literature reviewed, and its practical implications for HR system design and governance.

5.2.1 Domain 1: Algorithmic Control Variables (Input Layer)

The first domain of the IAHEBF captures the structural properties of algorithmic HRM systems that constitute the primary causal inputs into the chain of effects documented in Chapter 4. Five critical variables are identified within this domain:

- Algorithmic Opacity (AO): The degree to which the decision logic, evaluation criteria, and data sources employed by algorithmic HR systems are transparent and intelligible to affected workers and HR practitioners. High opacity (low transparency) is associated in the literature with elevated procedural injustice perceptions, reduced organizational trust, and heightened algorithmic anxiety. The IAHEBF treats opacity as a continuously variable input parameter that organizations can design toward or away from, rather than an inherent characteristic of algorithmic systems.
- Surveillance Intensity (SI): The degree of comprehensiveness, continuity, and granularity of algorithmic monitoring of worker behavior. Research reviewed in Chapter 4 establishes a curvilinear relationship between surveillance intensity and work performance: moderate performance monitoring is associated with accountability and quality improvement, while high-intensity continuous surveillance is associated with stress, presenteeism, creative inhibition, and eventual burnout. The IAHEBF treats surveillance intensity as a design variable for which optimal ranges, specific to work context and worker characteristics, can be identified.
- Autonomy Constraint (AC): The degree to which algorithmic systems limit worker discretion over task execution, interaction approach, work pace, and behavioral expression. As documented extensively in the gig economy literature, high autonomy constraint is a robust predictor of adverse well-being outcomes, including both emotional exhaustion and reduced work meaning. The IAHEBF incorporates autonomy constraint as a mediating variable: its effects on emotional labour intensity are moderated by the degree to which algorithmic transparency allows workers to understand the rationale for their constrained choices.
- Algorithmic Bias Risk (ABR): The structural potential of algorithmic HR systems to generate discriminatory outcomes across demographic dimensions, as analyzed in section 4.4. The IAHEBF treats algorithmic bias risk as a design parameter that can be systematically assessed and mitigated through bias auditing, diverse training data curation, and differential impact monitoring, and whose unmitigated presence produces both direct equity harms and indirect organizational costs including legal risk, reputational damage, and talent attrition among affected groups.
- Decision Reversibility (DR): The degree to which algorithmically generated employment decisions—hiring exclusions, performance assessments, scheduling allocations, deactivations—can be contested, reviewed, and reversed through accessible human processes. Low decision reversibility is among the most potent sources of algorithmic distress documented in the literature, as it combines the psychological harm of adverse outcomes with the compounded harm of permanent procedural exclusion.

5.2.2 Domain 2: Emotional Labour Dimensions (Mediating Layer)

The second domain of the IAHEBF captures the emotional labour processes through which the algorithmic control variables in Domain 1 are translated into the organizational and individual outcomes represented in Domain 4. This domain is specifically designed to import the theoretical sophistication of the emotional labour literature into the analysis of Algorithmic HRM, addressing the gap identified in Chapter 2.

- Surface Acting Intensity (SAI): The degree to which workers in algorithmically managed environments engage in surface acting—the management of outward emotional expression without corresponding internal regulation. In algorithmic contexts, surface acting is intensified by script rigidity, continuous monitoring, and the elimination of human supervisory empathy. The IAHEBF treats surface acting intensity as the primary pathway through which algorithmic control variables produce emotional dissonance and, ultimately, burnout.
- Deep Acting Availability (DAA): The degree to which the features of algorithmically managed work environments permit workers to engage in deep acting—the more effortful but potentially more sustainable form of emotional regulation involving genuine internal state modification. The IAHEBF proposes that interventions designed to reduce algorithmic rigidity and increase worker autonomy will, by expanding deep acting availability, partially buffer the emotional dissonance effects of algorithmic control.
- Emotional Dissonance Level (EDL): The degree of tension between felt and displayed emotions experienced by workers in algorithmically managed environments. The IAHEBF treats emotional dissonance as the central mediating variable translating emotional labour demands into burnout outcomes, and as the dimension most directly addressable through organizational HR interventions.
- Emotional Recognition Gap (ERG): A novel variable introduced in the IAHEBF, representing the degree to which algorithmic performance evaluation systems fail to recognize, measure, or reward the emotional labour investment of workers. The ERG operationalizes the Invisible Injustice Paradox discussed in section 4.2.1 and provides a theoretically grounded construct for research examining the relationship between algorithmic evaluation systems and worker motivation, engagement, and organizational commitment.

5.2.3 Domain 3: HR Interventions (Moderating Layer)

The third domain of the IAHEBF captures the organizational HR interventions that moderate the relationships between the algorithmic control variables (Domain 1), the emotional labour processes (Domain 2), and the organizational and individual outcomes (Domain 4). This domain operationalizes the preventive and remedial HR practices analyzed in section 4.7, while extending that analysis through theoretically grounded specification of the mechanisms through which interventions exert their effects.

- Algorithmic Governance Structures (AGS): Formal organizational mechanisms for the oversight, auditing, and accountability of algorithmic HR systems, including algorithm review committees, bias auditing procedures, transparency reporting requirements, and worker representation in algorithmic system design and modification. AGS interventions address the Algorithmic Opacity and Algorithmic Bias Risk variables in Domain 1, producing direct reductions in their adverse effects on emotional labour and outcomes.

- Human Connection Preservation (HCP): Organizational policies and practices designed to preserve meaningful human relationships within algorithmically managed work environments, including dedicated human HR contact points for employee concerns, regular manager-employee dialogue practices that supplement rather than merely defer to algorithmic data, and peer support programs. HCP interventions address the emotional recognition gap and autonomy constraint variables, providing the human acknowledgment of emotional labour that algorithmic systems structurally cannot provide.
- Emotional Labour Support Programs (ELSP): Targeted organizational interventions specifically designed to recognize, support, and mitigate the psychological costs of emotional labour in digital work contexts. These interventions go beyond generic EAP provisions to include emotion work recognition in compensation structures, training in emotion regulation skills adapted to digital work environments, and recovery time allocations that acknowledge the resource depletion dynamics of emotional labour.
- Autonomy Enhancement Mechanisms (AEM): System design and policy interventions that expand worker discretion within algorithmically managed environments, including flexible protocol interpretation, personalized interaction style permissions, and worker-controlled monitoring opt-in/opt-out capabilities. AEM interventions address the autonomy constraint variable in Domain 1, and the IAHEBF predicts that their effects on emotional labour outcomes will be mediated by the degree to which expanded autonomy reduces surface acting requirements and increases deep acting availability.

5.2.4 Domain 4: Employee Outcomes (Output Layer)

The fourth domain of the IAHEBF captures the organizational and individual outcomes produced by the interaction of algorithmic control variables, emotional labour processes, and HR interventions. This domain is organized around the central research concerns that motivated the study.

- Emotional Well-Being (EWB): The individual-level state of psychological health, characterized by low emotional exhaustion, positive affect at work, and effective coping with work-related stressors. The IAHEBF predicts that EWB is principally determined by the interaction of emotional dissonance levels and emotional labour support programs: high dissonance without adequate support predicts deteriorating EWB, while adequate ELSP can buffer dissonance effects on EWB even in high-dissonance environments.
- Organizational Trust (OT): The worker's confidence in the organization's good intentions, competence, and procedural integrity in managing the employment relationship. The IAHEBF treats OT as a critical intermediate outcome that mediates the relationship between HR interventions and performance outcomes: interventions that enhance transparency, reduce bias risk, and preserve human connection will improve OT, and improved OT will in turn facilitate the psychological safety that underpins high performance and innovation.
- Burnout Risk Index (BRI): A composite indicator of the individual's current risk of experiencing clinical-level burnout, incorporating dimensions of emotional exhaustion, depersonalization, and reduced personal accomplishment. The IAHEBF treats BRI as the most important lagging indicator of Algorithmic HRM quality, and proposes its systematic monitoring—through valid, validated survey instruments—as a core component of responsible algorithmic HR governance.
- Productivity and Performance (PP): The organization-level output outcomes of HRM quality, measured through productivity metrics, quality indicators, innovation rates, and service quality measures. The IAHEBF explicitly models PP as an outcome jointly determined by algorithmic efficiency and human well-being: the assumption that algorithmic management

produces superior performance outcomes by optimizing measurable productivity metrics ignores the evidence that high BRI, low OT, and low EWB systematically erode the human dimensions of performance—creativity, discretionary effort, customer relationship quality—that algorithmic metrics do not capture.

5.3 Framework Diagram and Visual Model

Figure 5.1: Integrated Algorithmic-Human Emotional Balance Framework (IAHEBF)

DOMAIN 1 ALGORITHMIC CONTROL VARIABLES	DOMAIN 2 EMOTIONAL LABOUR DIMENSIONS	DOMAIN 3 HR INTERVENTIONS (MODERATING)	DOMAIN 4 EMPLOYEE OUTCOMES
AO: Algorithmic Opacity **SI:** Surveillance Intensity **AC:** Autonomy Constraint **ABR:** Bias Risk Level **DR:** Decision Reversibility	**SAI:** Surface Acting Intensity **DAA:** Deep Acting Availability **EDL:** Emotional Dissonance **ERG:** Emotional Recognition Gap	**AGS:** Algorithmic Governance **HCP:** Human Connection Preservation **ELSP:** Emotional Labour Support **AEM:** Autonomy Enhancement	**EWB:** Emotional Well-Being **OT:** Organizational Trust **BRI:** Burnout Risk Index **PP:** Productivity & Performance
FEEDBACK LOOP: Outcome states (EWB, OT, BRI) feed back into Domain 1 via organizational learning and system adaptation			

Source: Original framework developed by researcher. IAHEBF = Integrated Algorithmic-Human Emotional Balance Framework

Table 5.1: IAHEBF Framework Component Summary and Operationalization

Domain	Variable	Definition	Measurement Proxy	Direction of Effect
D1	Opacity (AO)	Degree of algorithmic decision logic inaccessibility	Transparency audit score; worker comprehension surveys	High AO → High EDL
D1	Surveillance (SI)	Continuity and granularity of worker behavioral monitoring	Monitoring tool scope; worker-reported surveillance perception	High SI → High SAI
D1	Autonomy (AC)	Degree of worker discretion constraint by algorithmic systems	Work design audit; autonomy perception scale	High AC → Low DAA
D2	Surface Acting (SAI)	Frequency and intensity of emotion suppression/modification	EL Scale (Brotheridge & Lee, 2003)	High SAI → High EDL
D2	Recognition Gap (ERG)	Divergence between EL investment and algorithmic recognition	Perceived fairness of evaluation; invisible work survey	High ERG → Low OT

Domain	Variable	Definition	Measurement Proxy	Direction of Effect
D3	Governance (AGS)	Formal oversight mechanisms for algorithmic HR systems	Governance maturity index; audit completion rate	High AGS → Low ABR
D3	Human Connect (HCP)	Preservation of meaningful human HR relationships	Human touch index; HR accessibility survey	High HCP → Low ERG
D4	Well-Being (EWB)	Individual emotional health state in work context	MBI Emotional Exhaustion sub-scale; PERMA profile	Outcome variable
D4	Burnout Risk (BRI)	Composite burnout probability indicator	Maslach Burnout Inventory (MBI); Oldenburg Burnout Inventory	Outcome variable

Source: Developed by researcher based on thematic synthesis of reviewed literature

5.4 Theoretical Contribution of the IAHEBF

The Integrated Algorithmic-Human Emotional Balance Framework makes several theoretically original contributions that distinguish it from existing models in both the algorithmic management and emotional labour literatures.

First, the IAHEBF achieves the first systematic integration of emotional labour theory with algorithmic management theory within a single conceptual model. Existing research has examined these phenomena in parallel but has not produced a framework that specifies the mechanisms through which algorithmic control variables translate into emotional labour outcomes, and through which those outcomes in turn produce organizational consequences. The IAHEBF's domain architecture—with the emotional labour dimensions explicitly positioned as the mediating layer between algorithmic inputs and organizational outputs—provides this mechanistic specification.

Second, the IAHEBF introduces the Emotional Recognition Gap (ERG) as an original construct—not previously theorized in either the emotional labour or algorithmic management literatures—that captures the distinctive injustice of invisible emotional work in algorithmic contexts. The ERG bridges Hochschild's (1983) original insight about the undervaluation of emotional labour with the specific features of algorithmic evaluation systems that produce a structurally novel form of that undervaluation. This construct is theoretically grounded, empirically researchable, and practically actionable.

Third, the IAHEBF's treatment of HR interventions as moderating variables—rather than merely as organizational responses to problems already caused—reflects a preventive orientation that is central to the framework's practical value. By specifying the mechanisms through which interventions moderate the relationships between algorithmic control variables and emotional labour outcomes, the IAHEBF enables organizations to calculate the expected benefit of specific interventions before deployment, rather than discovering the human costs of algorithmic HR systems after the fact.

Fourth, the IAHEBF's incorporation of a feedback loop from organizational outcomes to system design reflects a systemic, learning-oriented perspective that distinguishes it from static models. The recognition that poor emotional well-being outcomes, high burnout rates, and eroded organizational trust will feed back into algorithmic system performance—through attrition, engagement deficits, and the erosion of the human capital that algorithmic systems are designed to manage—provides a self-contained economic argument for human-centered Algorithmic HRM design that does not rely on ethical imperatives alone.

For HR practitioners, the IAHEBF provides a structured framework for conducting organizational assessments of algorithmic HR system adequacy, designing intervention portfolios that address the full spectrum of algorithmic HR challenges, and monitoring outcomes in ways that capture both the efficiency dimensions that algorithmic systems are designed to optimize and the human dimensions that they tend to ignore. The framework's modular architecture allows it to be applied in full or in part depending on organizational context, with each domain providing a self-contained analytical contribution while gaining additional explanatory power through integration with the others.

CHAPTER 6: CONCLUSION

6.1 Summary of Key Insights

This research has conducted a systematic, analytically rigorous examination of the challenges inherent in Algorithmic Human Resource Management through the integrated lens of emotional labour theory, organizational justice, burnout scholarship, and critical digital studies. The principal insights emerging from this inquiry can be summarized along three dimensions.

At the empirical level, the review of existing research has established, with substantial evidentiary weight, that the deployment of algorithmic systems in HRM generates systematic and predictable adverse consequences for worker emotional well-being, organizational trust, and the distribution of employment equity. These consequences are not random or peripheral but are structurally produced by specific features of algorithmic management—opacity, surveillance intensity, autonomy constraint, and decision irreversibility—that are present to varying degrees across the organizational contexts examined. The evidence from platform economy contexts is particularly compelling: workers managed by comprehensive algorithmic systems in the gig economy experience rates of emotional exhaustion, burnout, and algorithmic anxiety that significantly exceed those observed in comparably demanding traditionally managed work environments.

At the theoretical level, this research has established that the emotional labour framework—Hochschild's foundational theory of the psychological costs of managed feeling—requires systematic adaptation to remain analytically adequate to the novel conditions of algorithmically mediated work. The adaptation offered in this research, centered on the concept of the Emotional Recognition Gap and the elaboration of surface and deep acting dynamics specific to algorithmic contexts, extends the explanatory reach of emotional labour theory while honoring its foundational insights. The parallel adaptation of algorithmic management theory—by grounding its structural observations in the psychological mechanisms of emotional regulation—moves both fields toward a more integrated account of the human experience of contemporary digital work.

At the practical level, the analysis has documented a significant gap between the sophistication of organizational algorithmic HR deployment and the adequacy of governance frameworks, worker protections, and HR interventions available to manage its consequences. This governance gap is most acute in the Global South, and most consequential for the most economically vulnerable workers—gig economy participants and platform workers—who face the highest algorithmic management intensity with the least institutional protection. Closing this gap requires action at multiple levels: organizational policy, HR system design, regulatory frameworks, and scholarly research.

6.2 Linkage to Research Objectives

This study's research objectives have been systematically addressed through the preceding chapters. The first objective—critical examination and synthesis of existing literature—has been realized through the extensive thematic literature review in Chapter 2, which identified dominant theoretical frameworks, documented empirical trends, and mapped research gaps in a structured Literature Gap Table. The second objective—thematic analysis of secondary data to identify and analyze core challenges—has been realized through the comprehensive thematic analysis in Chapter 4, which developed a six-theme framework capturing the principal dimensions of the Algorithmic HRM challenge and synthesized supporting evidence across diverse empirical studies.

The third objective—analysis of differential impacts across worker populations—has been addressed through the specific attention given in Chapter 4 to the distinct experiences of gig economy workers, women, racial minorities, and workers in the Indian and broader Asian context, with the algorithmic bias analysis in section 4.4 providing particular depth on the equity dimensions of differential impact. The fourth objective—evaluation of organizational and policy responses—has been realized through section 4.7's critical assessment of documented interventions against evidence-based effectiveness criteria. The fifth objective—development of an original conceptual framework—has been realized through Chapter 5's presentation of the IAHEBF, its detailed component specifications, its visual representation, and its theoretical contribution analysis.

6.3 Strategic Implications

The strategic implications of this research span organizational, policy, and scholarly domains. For organizations deploying algorithmic HR systems—currently the majority of large employers and the rapidly growing class of platform economy operators—the findings of this research provide a clear and evidence-based strategic imperative: algorithmic efficiency gains realized at the cost of worker emotional well-being, organizational trust, and employment equity are not simply ethically problematic; they are strategically unsustainable. The human capital costs of high burnout rates, elevated attrition, disengaged workforces, and eroded organizational trust—all documented consequences of inadequately governed algorithmic HRM—systematically erode the organizational performance that algorithmic efficiency is intended to enhance.

The IAHEBF framework provides a practical instrument for translating this strategic insight into action: organizations can use the framework's domain architecture to audit their current algorithmic HR systems against the full spectrum of human-centered criteria, identify the highest-priority intervention opportunities, and design monitoring systems that capture both efficiency and well-being outcomes in integrated organizational performance metrics. The framework's specific recommendation for human-in-the-loop governance mechanisms, Emotional Labour Support Programs, Human Connection Preservation policies, and Autonomy Enhancement Mechanisms provides an actionable intervention portfolio grounded in both theoretical adequacy and evidence-based effectiveness.

For policy makers and regulatory bodies—including the Indian Ministry of Labour and Employment, NITI Aayog's work on gig economy governance, and international bodies including the ILO and OECD—the research provides analytical foundations for evidence-based regulation of algorithmic HR practices. The specific recommendation that emerges most clearly from the analysis is for mandatory algorithmic transparency requirements in employment contexts: workers managed by algorithmic systems have a right to know the criteria by which they are evaluated, the data on which those criteria are applied, and the processes through which adverse algorithmic decisions can be contested and reversed. This recommendation aligns with the approach taken by the EU AI Act and could form the basis for analogous frameworks in the Indian regulatory context.

For the academic community, the IAHEBF framework provides a theoretically grounded platform for future empirical research. Primary studies testing the framework's hypothesized relationships—particularly the mediating role of the Emotional Recognition Gap and the moderating effects of Human Connection Preservation on the relationship between Surveillance Intensity and emotional exhaustion—would advance both theoretical knowledge and practical guidance for organizations navigating the increasingly urgent challenges of Algorithmic HRM in the twenty-first century workplace.

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ANNEXURES

Annexure A: Glossary of Key Terms

Term	Definition
Algorithmic HRM	The deployment of artificial intelligence and machine learning algorithms to automate or augment human resource management decisions including hiring, performance evaluation, scheduling, and workforce monitoring.
Emotional Labour	The management of feeling to create a publicly observable facial and bodily display, as a requirement of employment (Hochschild, 1983).
Surface Acting	The modification of outward emotional expression without corresponding change in internal emotional states, creating emotional dissonance.
Deep Acting	The modification of internal emotional states to align with display requirements, involving greater cognitive effort but potentially less dissonance.
Algorithmic Opacity	The inaccessibility to workers and HR practitioners of the decision logic embedded in algorithmic HRM systems.
Emotional Dissonance	The psychological tension arising from a discrepancy between felt emotions and the emotions required to be displayed by organizational norms.
Burnout	An occupational syndrome characterized by emotional exhaustion, depersonalization, and reduced personal accomplishment (Maslach & Leiter, 2016).
Psychological Safety	The shared belief that the work environment is safe for interpersonal risk-taking, including expression of concerns and mistakes (Edmondson, 1999).
Gig Economy	A labor market structure in which short-term contracts and freelance work are prevalent, typically mediated by digital platforms.
IAHEBF	Integrated Algorithmic-Human Emotional Balance Framework: the original conceptual framework proposed in this research to guide ethical and emotionally intelligent Algorithmic HRM design.
Algorithmic Bias	The systematic production of discriminatory or unfair outcomes by AI decision systems, typically arising from biased training data or proxy variables.
Emotional Recognition Gap	The divergence between the emotional labour investment of workers and the degree to which that investment is recognized or rewarded by algorithmic evaluation systems.

Annexure B: Summary of Key Case Studies Referenced

Organization	Algorithmic HR System	Key Challenge Documented	Primary Source
Uber	Algorithmic dispatch, surge pricing, star rating system	Driver income manipulation through information asymmetry; rating-based coercion of emotional performance	Rosenblat (2018)
Amazon	Picking rate tracking, AI resume screening, warehouse robotics	Unsustainable algorithmic pacing; gendered bias in AI recruitment system	Delfanti & Faber (2022)
Swiggy/Zomato	Delivery algorithmic dispatch, customer rating, incentive systems	Income insecurity amplifying emotional distress; absence of HR support for delivery partners	Sarkar (2019); NITI Aayog (2022)
TaskRabbit	Matching algorithm, reputation scoring, pricing	Hypercompetitive rating environment producing chronic emotional labour and anxiety	Wood et al. (2019)
IBM Watson Tone Analyzer	AI sentiment analysis of customer service interactions	Cultural and demographic bias in emotion recognition; differential scoring outcomes	Buolamwini & Gebru (2018)