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Factors Affecting Employee Decision Making in an AI Environment

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***Abstract*—**The decision-making process in humans is a complicated system influenced by a variety of intrinsic and extrinsic factors. Human decisions have a ripple effect on subsequent decisions. In this study, the scope of human decision making is limited to employees. In an organisation, a person makes a variety of decisions from the time they are hired to the time they retire. The goal of this research is to identify various elements that influence decision making. In addition, the environment in which a decision is made is a significant aspect of the decision-making process. Employees in today's workplace use artificial intelligence (AI) systems for automation and decision augmentation. The impact of AI systems on the decision-making process is examined in this study. This research is designed based on a systematic literature review. Based on gaps in the literature, limitations and the scope of future research have been identified. Based on these findings, a research framework has been designed to identify various factors affecting employee decision making. Employee decision making is influenced by technological advancement, data-driven culture, human trust, decision automation-augmentation and workplace motivation. Hybrid human-AI systems require development of new skill sets and organisational design. Employee psychological safety and supportive leadership influences overall job satisfaction.

***Keywords*—**Employee decision making, artificial intelligence, environment, human trust, technology innovation, psychological safety.

I. Introduction

HUMAN by nature is a social animal. His belief systems, values, attitudes, and behaviours are defined and influenced by the interaction with environment, in which he operates. In an organizational context also, environment plays a major role. The work environment has a positive influence on employee engagement and decision making [15]. In current times, machines and humans are working collaboratively to increase productivity and improve ease of work, when monitored effectively with smart people analytics [13].

Human decision making is a complex process and AI is influencing various areas of workplace and human resources (HR), e.g., task characteristics, knowledge characteristics, social characteristics and job demand. Task characteristics include autonomy, job feedback, task significance, task variety and role clarity. Knowledge characteristics include job complexity and problem-solving. Social characteristics include social support, and job demands include workload, physical demands, emotional demands and job insecurity [27].

Positive impacts of an AI-enabled work environment include work-related flexibility, autonomy, creativity, innovation, enhanced job performance and enhanced creative thinking. It supports awareness about context, self-organising, communication and reasoning abilities [23]. However, unintended consequence of AI development, such as data leaks and security breaches, can be drastic [23]. Hence, relationships between managers and workers will keep reconfiguring with the application of AI [14].

Training and development for the gig economy are crowdsourced on digital platforms. Task performance and platform literacy are the focus of training and development [36].

The technically opaque nature of AI systems (deep learning) and organisational intent to minimise the public disclosure of decision making may result in deflected accountability [14]. AI will create constant surveillance at work [5]. Technology influences team performance which in turn decides which technology will be adopted. Electronic performance monitoring improves performance for simple tasks but is unclear for complex tasks [19].

The perception of interpersonal justice is stronger with a human agent. With no explanation, AI reduces perception of justice with a human agent and no change with an automated agent. Human agents are considered to be more individualised and automated agents more consistent and less biased [31].

A. Research Problems and Questions

Research problems for this paper have been identified from gaps found while doing a systematic literature review. The questions raised are the following:

a) What is the influence of technology innovation on employee decision making?
b) How does data driven culture affect employee decision making?
c) What is the impact of human trust on employee decision making?
d) Does decision automation affect employee decision making?
e) How does workplace motivation affect employee decision making?

B. Research Objectives

To answer the above questions, the following objectives have been identified:

a) To identify the influence of technology innovation on employee decision making.
b) To establish the impact of data driven culture on employee

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decision making.

c) To ascertain the impact of human trust on the employee decision making process.
d) To evaluate the impact of decision automation on employee decision making.
e) To assess the effect of workplace motivation on the employee decision making process.

C. Scope of the Study

There are various decisions made by an employee in an organisation from hiring to retirement. All decisions affect organisational performance and outcomes. Post-pandemic, many organisations are shifting their focus to the employee experience and people strategies as a critical step to achieving their business strategies. The scope of this study is to identify and establish the factors which affect employee decision making in an AI environment and their impact. This will help design interventions for rational decision making.

II. Literature Review

Human intelligence and AI are complementary to each other; hence the future is hybrid human-AI systems [3].

Perceived trustworthiness improves trust in both human and automated leadership. Human leadership agents are considered more compassionate and flexible. Integrity and transparency are higher under automates leadership. Overall, human leadership agents are more trustworthy [12].

Humans are prone to systematic biases; however, AI systems are also not free from such biases. There are three main categories of biases: data bias, method bias and societal bias. data bias can be due to selection bias, homogeneity bias or sample unit bias. Method bias can be due to overgeneralisation, confirmation bias, automation bias or correlation fallacy. Societal bias can be due to historical bias, stereotypical bias, implicit association or prejudice [1].

This systematic literature review identifies various parameters influencing employee decision making in an AI environment. The following five parameters have been identified and will be discussed further:

a) Technology innovation.
b) Data driven culture.
c) Human trust.
d) Decision automation.
e) Workplace motivation.

A. Technology Innovation

Technology exposes decision-making biases in human beings. The high cognitive load of information leads to less-than-optimal decisions. For ease of use and adoption, technology provides default options. In turn, this creates the bias for defaults [6].

Not all decisions are made by technology alone. In many scenarios, technology acts as a support system to the decision-making process. The high autonomy of decision support systems leads to high information load reduction, which increases the uncertainty and ambiguity of decisions being made. This in turn increases technostress, resulting in decreased intention to use decision-support systems [35]. The disparity between a technology's capabilities and a person's awareness or knowledge of that technology's actions is defined as technostress [35].

For the adoption of technology, suitable organisational design and organisational learning is helpful [16]. Earlier machines were used as a tool. The same understanding is not suitable for AI. For AI, there is a need for role change to interpreter or translator [34]. Organisations focused on aligning HR strategy with business strategy experience high discontinuity created by digital transformation. This requires a shift to actionable high-impact analytics [24].

AI for HR is still in its early stages. Workers' power and autonomy are eroding because of the use of technology. As a result, AI is lowering the quality of work [5]. HR workspace is evolving as a result of shifting skill sets and capabilities [23]. To build ownership and accountability for ROI, HR Analytics (HRA) should be incorporated into HR functions rather than as an IT project [32].

B. Data Driven Culture

AI technology improves employee performance in a variety of ways. However, in order to achieve this, AI awareness and training are essential [29]. Technological training and job skills positively influence perceptions and reactions towards decision support systems in AI [35].

Expectations of AI systems in terms of decision-making performance, effort necessary for system use, personal growth concerns, personal well-being concerns, and perceived threats influence attitudes toward AI and, as a result, intentions to use AI systems [4].

AI technology helps with problem solving, effectiveness, training and feedback [29]. However, pure data-driven logic may not always result in the best decisions, which means maximisation of a single parameter at the expense of morality, values and ethical norms. As a result, managers face a personal challenge in developing and training complementary skills as objective tasks are replaced by algorithms [16]. AI should not take over HR's essential functions and meaning [29].

C. Human Trust

Integration of AI into an organisation is influenced by the employee's trust in AI technologies. Transparency establishes cognitive trust. Transparency is the explainability and reliability of AI [10]. Explainability of AI builds trust for decisions made by machines [11]. Reliability and trust in AI are a complex phenomenon, which is why low reliability does not always result in low trust [10]. In the instance of relational inducement, the perceived violation would be greater for the human agent, whereas in the case of transactional inducement, the opposite would be true [33]. Trust in AI is also dependent on the role of AI in an organisation. There would be high human trust for issues that do not require social or emotional intelligence. For robotic AI, high machine intelligence builds high trust. But, for embedded and virtual AI, high machine intelligence decreases trust [10].

The employment of AI systems shapes managerial cognition, because AI systems are thought to make better decisions, have a higher level of trust, and have a more structured procedure [17]. However, concerns about personal well-being (anxiety and tension with AI use) and development (prevention of learning from own experience) influence intent to use [4].

People perceive systems to have less bias than humans [20]. But AI and ML developers prioritise automation over augmentation [5]. Algorithmic decision making can reinforce the biases of the past [16], resulting in development not being free from biases. Hence, social science needs to be linked with computer science to avoid biases in the systems [5]. In an organisation, power shifts in decision making can also lead to biases in AI [34].

There is a higher level of acceptance for objective and analytical task output because AI systems are thought to surpass humans in this area [17], but when people are not sure about the ability of humans to use a decision automation/augmentation system, they may doubt these systems [20]. Negative perception about algorithms, lack of emotional trust and fear of change increase the algorithm aversion [22] whereas, a high level of job experience will likely generate more trust and reliance on an autonomous decision support system (DSS) [35].

The user forms psychological bonds with the agents, whether human or algorithmic [33]. Users' perceptions of threats are influenced by perceived severity and susceptibility. Perceived severity refers to a person's estimation of the amount of harm AI can cause, whereas perceived susceptibility refers to the possibility of it happening [4]. In the case of AI systems, high involvement with the user interface creates attachment for decision making. Low human involvement detaches the decision maker from decisions and creates spatial and temporal separation, rational distancing and cognitive displacement [2].

D. Decision Automation

The utilisation of data and collaboration between the decision maker and analytics results in 'collaborative rationality,' which leads to better decisions [9]. In decision making, intentions as choice architects and the availability of cognitive resources play an important role [25]. Smart nudging improves decision making by providing cognitive resources, data and extending engagement [25]. System characteristics influence an employee's affective and cognitive reactions [35].

The greatest benefit from AI decision making is achieved when it augments managerial decision making [20]. Decision automation/augmentation systems affect perceived accountability and responsibility for the decisions being made [20]. People perceive less responsibility of outcome if reduced autonomy of decisions exists [31]. Users are also less prone to questioning the decisions of automated agents. Hence, there is less discovery of errors and biases and accountability remains unclear [31].

Decision automation/augmentation systems are affected by second and third parties. Second parties are the ones who are affected by the decisions being made and third parties are observers. Fairness, trust, controllability, responsibility and autonomy are all influenced [20]. Human managers accept the use of machines in decision making if the weight of humans is higher. The saturation limit of humans in decision making is 70%. Some managers prefer equal partnership with machines and some managers prefer to give the upper hand to machines [11]. Reactions to decision augmentation and automation is affected by system configuration, understandability and transparency through information and explanations [20].

E. Workplace Motivation

AI improves the quality of HR decisions [29]. Algorithmic management is affecting various areas of the workplace, e.g., goal setting, monitoring, scheduling, performance management, compensation and job termination [27]. AI works as a horizontal facilitator rather than a vertical functional silo [16]. Complexity, perceived usefulness, data quality, access to relevant data, and compatibility are all technological aspects that influence HRA adoption [32].

Integration of AI will shift roles. Employees and managers should be trained on empathy, creativity and emotions. Diverse team members need to be chosen who have the necessary skills for strategic decision making and AI usages [34]. Otherwise, lack of balanced human involvement leads to deferred decisions, workarounds and manipulations [2]. As AI transfers agency and control from humans to technology, a new human-technology relationship emerges. Companies will need to change their workforce structure, organisational structure, job design, decision-making processes, and knowledge management systems in the future [10].

The employee-employer relationship is influenced by algorithmic management, operating as a contract maker for the psychological contracts of employees. This connection is determined by the stage of employment and the degree of underdelivery by the agency. Employer commitment is lowered as a result of algorithmic agents. When it comes to human agents, video chat outperforms text chat in terms of communicating greater employer commitment in relational inducements [33]. However, data-driven resources become less distinctive to a given organisation and more imitable over time, lowering a company's competitiveness. As a result, when combined with analytics-based HRM, intuition-based HR management can provide a more long-term competitive edge. Organisations will have to make or balance trade-offs between efficiency owing to data-driven decision making and idiosyncratic knowledge for domain insights [18].

III. Proposed Methodology

This study is based on critical review of articles from 2020–2022. The articles were identified from Google Scholar, Proquest and other international journals. Based on research objectives, articles were critically reviewed to identify the current body of knowledge in this area and research gaps were identified for this study.

The systematic literature review involved careful identification of gaps, cataloguing the articles as per identified independent variables and the selection of five independent variables as per the frequency distribution of gaps. A research framework was created and propositions were developed and analysed.

IV. Research Framework

As per systematic literature review, a conceptual framework is proposed with five independent variables: technology innovation (TI), data driven culture (DC), human trust (HT), decision automation (DA) and workplace motivation (WM), with employee decision making (ED) as dependent variable. This is detailed in Fig. 1.

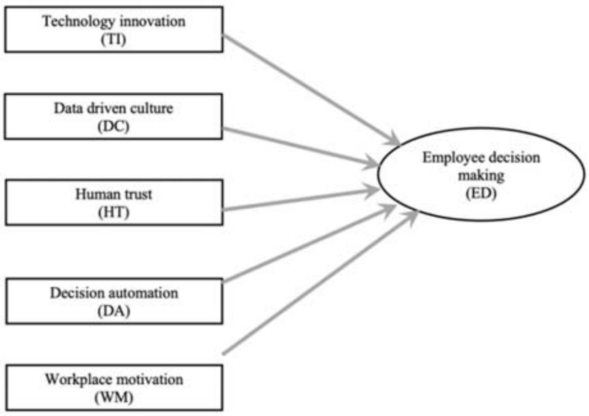

Fig. 1 Research Framework

V. Discussion, Analysis, Outcome and Propositions

A. Technology Innovation

Discussion: Technology can expose decision-making biases, cause technostress, and lessen the desire to use the system. As a result, rather than being employed solely for automation, AI technologies should be used collaboratively for decision augmentation.

AI is viewed through the lens of increasing productivity. It can be utilised for a broad viewpoint of optimisation, where technological innovation can be used to optimise a variety of human objectives [7].

Strategic decision-making is aided by combining AI and human intellect. Instead of viewing AI as a tool, successful integration necessitates a shift in translation and interpreter roles. As a result, it necessitates a shift in skills and responsibilities [34].

Outcome: Porter’s generic strategies explain the sources of competitive advantage as differentiation and cost. Business model innovation creates advantage both for cost and differentiation. Hence, business model innovation based on new technologies has positive influence on companies’ competitive advantage (financial and non-financial parameters) [8].

Proposition 1: TI has a significant relationship with ED in an AI environment through cognitive load, autonomy, technostress, skill set and intention to use AI systems, which results into an outcome of competitive advantage.

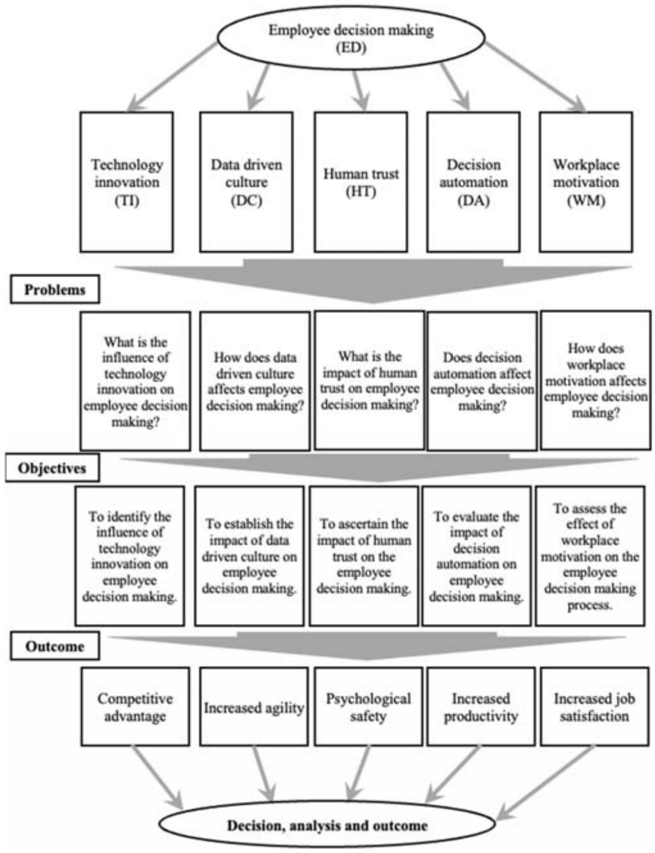

Fig. 2 Research Framework - Discussion, Analysis and Outcome Measures

B. Data Driven Culture

Discussion: Improved awareness, technical training and job skills positively help perception about AI systems. Intention to use AI systems is influenced by perceived threat, performance, effort and personal well-being concerns. AI technology helps in cognitive tasks which need to be balanced with morality, values, etc. Working collaboratively with AI requires new skill developments.

An empirical study done in China indicates that AI will be affecting the skill structure in organisations [21].

Strong ED skills positively influence employee empowerment and in turn employee performance. A continued learning culture also empowers employees and improves employee performance. With continued learning and strong decision-making skills, employees will proactively identify problems and solve them with confidence, bringing agility to the organisation [30].

Outcome: Stretching current resources to do new things or embrace new ways of functioning is what organisational flexibility is all about. Organisational fixedness, on the other hand, identifies what should be maintained the same to allow for faster changes. With the correct combination of flexibility and fixedness, organisations can become more agile.

Proposition 2: DC has a significant relationship with ED in an AI environment through perceived threat, expectation from AI systems, perception for use of AI, ethical norms and awareness of AI systems, which results into an outcome of increased agility.

C. Human Trust

Discussion: Trust in technology influences adoption. However, the relationship is dependent on various other factors, including transparency, relational inducement, transactional inducement, the role of AI in an organisation, emotional intelligence, human biases and biases in AI systems. People perceive that AI systems have fewer biases, hence there is high confidence in analytical tasks and more forgiveness for errors done by AI systems. But AI systems are also prone to systematic biases, hence social science needs to link with computer science in the development process.

Reducing algorithmic biases requires context which is difficult to achieve from only a technical perspective, hence a cross-disciplinary approach is needed [38].

Inclusive leadership improves take-charge behaviour. It happens in two stages. In the first stage, it is due to psychological safety and in the second stage it is due to thriving at the workplace [39].

Outcome: Leader behaviour, group dynamics, trust and respect, practise fields, and a supportive organisational setting all contribute to workplace psychological safety.

Proposition 3: HT has a significant relationship with ED in an AI environment through user involvement, cognitive trust, psychological bond, managerial cognition and perceived bias, which results into an outcome of psychological safety.

D. Decision Automation

Discussion: The greatest benefit occurs when DA augments managerial decision making. In decision making intentions such as choice architects and smart nudging, affective and cognitive reactions play an important role. People take less responsibility if they have less autonomy. People ask fewer questions of AI biases, hence there is less discovery of biases in AI.

Intelligent Augmentation (IA) has real-world applications as it considers creating value for humans, human factors, and has a multidisciplinary approach [40].

AI positively influences employee performance and work engagement. Changed leadership positively moderates these relationships [37].

Outcome: Productivity is defined as the integration of quantity, quality, and efficiency. Quantity refers to performing a large amount of work. Quality is defined by the finished work's excellence. And eliminating wasted labour is an example of efficiency.

Proposition 4: DA has a significant relationship with ED in an AI environment through collaborations, choice architects, nudging, decision augmentation and understandability, which results into an outcome of increased productivity.

E. Workplace Motivations

Discussion: Perceived usefulness, empathy, the human-technology relationship, the psychological contract, intuition-based HRM and idiosyncratic knowledge influence WM.

Remote working is enabled via internet services; hence the nature of the workplace is changing to a platform [28]. Leadership performance and supporting organisational culture positively influences trust in organisation, work engagement and overall job satisfaction [26].

Outcome: Mentally challenging work, supporting colleagues, supporting working conditions, equitable reward and personality job fit, influences job satisfaction.

Proposition 5: WM has a significant relationship with ED in an AI environment through perceived usefulness, empathy, human-tech relationship, psychological contract, intuition based HRM and idiosyncratic knowledge, which results into an outcome of increased job satisfaction.

VI. Research Implication

This study is qualitative research with structured reviews of articles. The study focuses on the ED process in an AI environment. The study provides many theoretical contributions. First, factors affecting ED are identified based on current gaps in literature including TI, data-driven decision making, HT, DA and WM. Second, it substantiates the future need for collaborative human-AI and IA. Third, it establishes the need for changes in organisational design, role design and skills development. Fourth, psychological safety in the workplace improves with inclusive leadership both for human and AI. Fifth, a supportive hybrid work culture, systems and leadership influences overall job satisfaction.

VII. Limitations and Scope for Future Research

Because the study is based on a structured literature review, it is limited to the consolidated articles that were considered. More publications reviewed could affect the conclusions reached in this study.

Five variables have been identified based on the articles evaluated. Other characteristics, such as perceived fairness, team dynamics, work performance, and accountability, can be considered in future research.

Future study could concentrate on developing hypotheses based on these assumptions and testing them using analytical approaches.

VIII. Conclusions

ED is critical for every firm because it not only affects employee strategy but also the overall corporate strategy. AI is rapidly evolving, and there is a strong leadership focus on adopting new technologies. These technologies, on the other hand, are primarily concerned with increasing efficiency. The workplace has changed dramatically as a result of the pandemic, remote employment, and hybrid working. There is a new human-AI connection to govern. With so many variables changing, it is critical for people to be trained in new abilities for collaborative AI work. For productive and rapid adoption of AI technologies, supportive leadership, workplace, and systems would be beneficial.

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