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A Comparative Study Between Team Decision Making and AI Decision Making: Implications for the Future

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A B S T R A C T

Artificial Intelligence has broad implications for humanity, and therefore vital for educational institutions to equip learners with the skills to navigate careers. The paper synthesises research on traditional and new tools for decision-making and presents implications that the future of AI holds for leaders and developed economies. The overall objective is to draw a comparison between traditional decision making and AI decision making in organisations. A total of 200 managers participated in the quantitative study. The results show that traditional decision making was preferred over AI decision making as it scored a higher mean value. The results of a multiple regression test also revealed that with the increase of the perceived threat of AI, managers' willingness to use AI increased. Given the circumstances that learning AI skills could advance a manager's career, then it led them to use AI. The implications of these results inform employers' strategic plans to implement learning and development initiatives while also informing governments about their impact on policymaking. Human resources traditionally used compensation and rewards to motivate employees in a change process. However, improving career prospects through the adoption of AI can create a favourable environment where the organisation can reap the benefits of AI and employees' development.

1. Introduction

Making decisions is the lifeblood of any organization (Groysberg & Abbott, 2020). In other words, decisions are required for its sustainability and continuity (Doumpos et al., 2022). The faster an organization can enact high-quality decisions, the greater the value delivered to stakeholders (Jin & Lei, 2023). Yet research has revealed that nearly 80 per cent of organisations struggle with decision making (Aminov et al., 2019). The environment in which an organization operates is never constant. It can change rapidly; therefore, it is imperative to have a long-term vision for an organization (Khan et al., 2021). Effective decisions by the management and teams align with the vision, organisational goals and objectives, as well as broader strategic objectives (Macdonald et al., 2018). Effective decision-making analyses information from environmental, societal and economic trends that contribute to a sustainable organization (Fleisher, 2020). It is these criteria that set apart a high-quality decision from a poor-quality one. Alshiki and Abdullah (2018) agree that the above criteria are pivotal to the decision-making process. But they also suggest that the quality of data used as input into decision making becomes a critical factor for high-quality decisions. While organisations possess large volumes of data, a data strategy should be developed which meets certain benchmarks to ensure high-quality data is integrated into decision making. These are the following:

- *Accuracy*: the extent to which data represents actual environmental conditions.
- *Integrity*: the consistency of data and its relationship with different variables.
- *Consistency*: data yields the same results over the period of decision-making.

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- *Complete*: all relevant data is present for decision making
- *Validity*: data fits into defined ranges.
- *Real-time*: data is produced as it occurs and is most recent. (Doval & Das, 2022)

The present research study aims to understand the use of AI in decision making and how this shapes the future of organisational decision making. This aim is fulfilled by the following objectives:

1. The first objective of the paper is to evaluate whether the traditional form of decision making, i.e. team decision making, is better than AI decision making.
2. The second objective is to evaluate the extent to which AI is a threat to an individual's career management path.
3. The third objective is to identify the effect of future AI trends on jobs and its implications for organisations, economies and government policymaking.

The next section discusses two forms of decision making, rational decision-making model as a form of traditional decision making and AI decision-making. A comparison is then made between the two.

2. Literature Review

2.1. Team Decision-making

Teams are effective in problem solving when they possess complementary skills. This is used in how a team functions in a workplace. Most commonly, teams make decisions using problem solving techniques using the rational decision-making model (Amico 2021). First, a team recognizes the existence of a problem. This is usually in response to a threat to the existence of the team or could be an opportunity that will result in higher performance and outcomes for the team. Second, the team defines the problem by identifying how, when and where members became aware of the problem. Third, members gather information from various sources and the environment to further understand the problem and verify that they correctly identified the problem. Fourth, teams develop alternative solutions. This can involve the process of brainstorming, asking questions, exploring the environment and records. Fifth, members select the best solution. They can revisit the first and second step to determine if the solution fits. Further, members identify the desired end state which is pinpointing what success looks like. They determine which alternative solution best fits the problem and discussing the consequences. There is a human element in this process which is active listening from members and respecting differing views. The team may vote for the best solution once a consensus has been reached. Sixth, implementing the solution would require planning and approval of resources. Finally, teams set parameters to evaluate the solution and if it the desired end state that was identified in step five (Uzonwanne 2023).

2.2. AI Decision-making

A common question about using AI in decision making concerns the nature of its underlying processes. AI decision making is of utmost importance when data processing is carried out completely or in part by an AI platform (Perifanis & Kitsios, 2023). AI can handle anomaly detection, data crunching, and complex analysis, and it can spot trends (Jarrahi, 2018). The final decisions are then either completely automated or taken over by the human end (Lai, 2021). Whether a decision must be AI-automated, augmented, or supported depends on two factors. First, the time limit within which the organization needs to decide. Secondly, the complexity of the decision (Starita, 2021). For instance, high-frequency stock trading may just take a few microseconds. Pay decisions may take a few weeks. It may even stretch up to a few months or years for strategic acquisitions or mergers (Raghabendra, 2022). Figure 1. below represents the flow of AI decision making. Usually, the person responsible for managing the AI will feed large data sets into the AI system. Then the AI system generates possible solutions according to set criteria (Algorithms). Managers in charge of decision-making review the

possible options and given input and their expertise regarding the problem or opportunity. Finally, a business decision is made and implemented (Coleson, 2019).

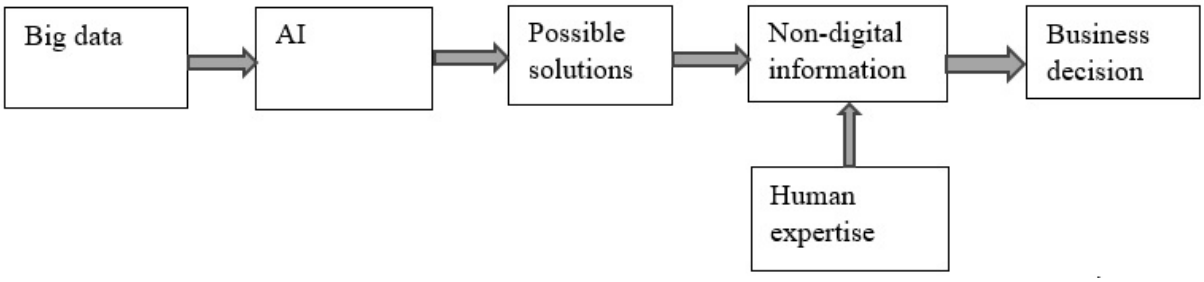


Figure 1. AI Model of Decision-making

An algorithm can be better explained as a set of instructions designed to solve specific problems or make certain decisions. They all function through a series of well-defined steps each contributing to an outcome desired by the organisation. An algorithm is created in response to an identified problem/opportunity in the organisation (Li et al., 2024). The problem's intricacies and requirements need to be clearly understood by the manager. To address the problem effectively, analysts utilize various tools, such as Python libraries, to conduct in-depth analyses. This approach helps them better understand the data structure and identify underlying patterns (Smith, 2023). Collaboration with IT is required to design an algorithm, that is, the step-by-step procedure to solve the problem. For this step, a flow chart can be used to visualise the algorithm flow and structure. Depending on the complexity of the problem the organisation can select an advanced tool such as PyCharm or visual studio for coding the algorithm. Implementing the algorithm means translating it into an understandable language for the manager which can be done using Java, Python or C++ tools (Crotts, 2024). Rigorous tests are conducted to verify that it solves the problem or makes the correct decisions. The development of the algorithm is well-documented to help other developers understand it. The algorithm is deployed and maintained regularly to ensure optimal functioning (Hall et al., 2022).

Data is usually collected from multiple sources including marketing data, performance data, employee feedback and other stakeholder inputs. These are fed into an AI system specifically customized with predetermined criteria and algorithms to generate meaningful information and possible solutions. An appointed committee of decision makers would review the business decision, providing their experiences and recommendations before implementing it (Schneider, 2020).

Because AI algorithms make decisions based on computational optimization, the 'space' wherein the decision is searched needs to be carefully specified and restricted in terms of the objective function. Consider, for example, an AI algorithm designed to propose to human decision-makers the 'best' candidate from a set of applicants. This process demands a specific definition of the desired qualities and characteristics that need to be optimized. Current AI algorithms typically identify patterns in data using automated search processes that result in an optimal prediction model. Such procedures do not provide a holistic explanation of how AI arrives at its decision (Shi et al., 2022).

2.3. AI Algorithms and Machine Learning Applications in Businesses

Businesses make use of algorithms for various business functions. In marketing, automation tools driven by algorithms search online for information according to predetermined inputs by the manager which provide valuable information that feeds the marketing and overall business strategy and decision making (Kumar, Ashraf and Nadeem, 2024). E-commerce can leverage marketing with automated reminders to customers. If a company's website sells a product, a manager wants to make sure they are optimizing sales by nudging customers who've abandoned their carts (Chugh and Jain, 2024). Every business needs to have aftersales services such as customer care. Organizing customer care using automatically generated help desk tickets can help a customer service team know the order they should respond to inquiries, and track the resolutions, saving time and preventing frustrated customers (Jain et al., 2023). As a financial function, managers often must follow up on unpaid

invoices. Algorithms can used to generate automated email reminders which can be sent out to clients with outstanding accounts (Liang, Jiang and He, 2024). A manager can have many administrative intense tasks to fulfil but cannot do so immediately. Algorithms can be set to automatically back up file at any time frequency either the end of the day or week (Parycek, Schmid and Novak, 2023). Project management software is helpful in managing to-do lists. It can generate reminders for tasks can prioritise tasks according to its urgency and importance. Timeframes can also be allocated to tasks which helps a manager identify the completion and as well as complexity of tasks (Bhanderi, 2024).

Machine learning is a subfield of artificial intelligence, which is broadly defined as the capability of a machine to imitate intelligent human behavior. Artificial intelligence systems are used to perform complex tasks in a way that is similar to how humans solve problems. The goal of AI is to create computer models that exhibit "intelligent behaviors" like humans (Chaudhari et al., 2023). Machine learning starts with data which can consist of numbers, photos, or text, like bank transactions, pictures of people or even bakery items, repair records, time series data from sensors, or sales reports. The data is gathered and prepared to be used as training data, or the information the machine learning model will be trained on. Larger sets of data will result in a machine learning more and becoming better to its intended function. From there, programmers choose a machine learning model to use, supply the data, and let the computer model train itself to find patterns or make predictions. Over time the human programmer can also tweak the model, including changing its parameters, to help push it toward more accurate results. A popular type of machine learning algorithm is a decision tree (Sarker, 2021).

2.5. Comparison Between Team Decisions and AI Decisions

Table 1. Comparison Between AI Decision Making and Team Decision Making

Decision-making criteria	AI Decision making	Team Decision making
Specificity of the decision search space	Requires a well-defined decision search space with specific objective functions (James, 2022).	Accommodates a loosely defined decision search space (Miller & Ireland 2005).
Interpretability of the decision-making process and outcome	The complexity of the functional forms can make it difficult to interpret the decision process and outcomes (Alijoyo et al., 2024).	Decisions are explainable and interpretable, through vulnerable to retrospective sense-making (Collins et al., 2023).
Size of the alternative set	Accommodates large alternative sets.	Limited capacity to uniformly evaluate a large alternative set (Inbar et al., 2011).
Decision-making speed	Comparatively fast. Limited trade-off between speed and accuracy (Jones, 2024).	Comparatively slow. High trade-off between speed and accuracy (Inbar et al., 2011).
Replicability of outcomes	Decision-making process and outcomes are highly replicable due to standard computational procedure (Bischoff, 2023).	Replicability is vulnerable to inter- and intra-individual factors such as differences in experience, attention, context, and emotional state of the decision maker (Johnson, 2021).

As the entire AI decision-making procedure is automated, identified patterns and models can have extraordinary complexity. Team decision-makers can more readily backtrack their reasoning steps and provide explanations and justifications for why they made a certain decision. Yet, while explanations or narratives of decision-making processes may be more comprehensible, they may not always be accurate, truthful, or comprehensive. As AI-based algorithms use an automated search for the best-fitting model, they can be used to evaluate the same set of objective functions uniformly and consistently over millions of alternatives. For example, once it is defined what constitutes the 'best' candidate, the same criteria can be autonomously and efficiently applied to evaluate millions of applicants (Shi et al., 2022).

Team decision making is limited by cognitive constraints that make it practically impossible to uniformly process large numbers of alternatives. When a large number of seemingly equivalent alternatives are available, team decision makers quickly become overwhelmed with the multitude of potential outcomes. Advances in computing hardware – particularly in general processing units and tensor processing units – and efficient algorithms have enabled AI-based decision making to occur at a near-instantaneous speed. The need to make speedy decisions can be detrimental to team decision-making outcomes. Under great time pressure, decision makers often utilize bias to overemphasize some and ignore other information, leading to a speed-accuracy trade-off. AI algorithms follow standard and non-ambiguous – though relatively inflexible – decision making processes that provide consistent outcomes given consistent inputs. Team decision-making, in contrast, involves inter- and intra-individual variance in experience, attention patterns, emotions, and information processing that influence the type of information individuals attend to, encode and retrieve when making decisions (Shin et al., 2023).

2.4. Research Model and Hypotheses

To achieve the research aim, the paper builds and tests a theoretical model to understand the factors and their effects on managers' attitudes and behavioural intentions towards using AI for decision making to determine which decision-making method is better. It is expected that using AI for decision making can be perceived to have both positive and negative impacts, yet the literature does not seem to offer any models that explain and predict IT adoption by considering both benefits and concerns. In summary, the research model is based on the following main considerations:

- Human-centred approach – Studying managers' behavioural intentions towards adopting AI for organizational decision making must follow the human-centred approach because of the unique nature of the human – AI partnership. Humans and AI cannot be treated as separate entities to make the partnership work. Therefore, the research model proposed should include human perceptions, concerns and attitudes (Kelly et al., 2023).
- Inclusion of both technology acceptance and avoidance factors – Using AI for organizational decision making has the potential to create both positive and negative impacts, that could influence managers' attitudes and behavioural intentions to either accept or avoid using AI (Chatterjee et al., 2021).
- Factors related to personal concerns – Using AI for organizational decision making may raise serious concerns among managers about their personal development and well-being, which could significantly influence managers' attitudes and behavioural intentions towards using AI (Schiavo et al., 2024).

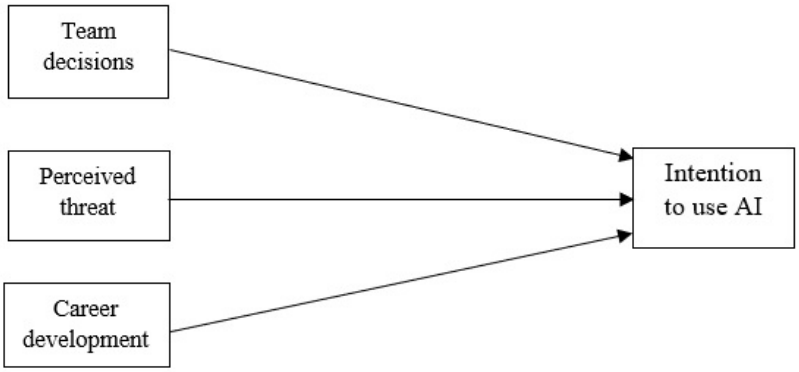


Figure 2: Independent Variables Influencing a Manager's Intention to use AI

Management Consulted (2023) agrees that AI was designed to assist with decision making when the data, parameters, and variables involved are beyond human comprehension. However, AI fails to capture or respond to intangible human factors that go into real-life decision making – the ethical, moral, and other human considerations that guide the course of business, life, and society at large (Heaven, 2020). Thus, the paper proposes the following two hypotheses:

Hypothesis 1 - Means and Frequency Distribution

a. H0a - Team decisions are not preferred to AI decisions.
b. H1b - Team decisions are preferred over AI decisions.

AI has progressed to compete with the best of the human brain in many areas, often with stunning accuracy, quality and speed. But can AI introduce the more subjective experiences, feelings, and empathy that make our world a better place to live and work, without cold, calculating judgment? This is where team decisions excel. They take into account personal experience, and diverse opinions and make employees feel part of the solution which provides a sense of belonging and value. The bottom line is that AI is based on algorithms that respond to models and data, often misses the big picture and most times cannot analyse the decision with the reasoning behind it (Riggio, 2022).

Perceived AI threats influence employee behaviour to avoid the threats or AI itself. It is evident throughout history that machines have largely replaced human efforts, particularly in industrial settings. In the digital world, AI has replaced human efforts where there is a degree of repetitiveness and tasks which can be easily automated. Tasks which do not require much thought can be replaced with AI. For example, on an assembly line, a worker who would weld doors to a car is now replaced with robotics and AI. A taxi driver is also at risk with the introduction of autonomous cars (Kieslich et al., 2021). Personal development concerns were measured using four self-developed indicators based on prior studies concerning the impact of AI-supported decision making on a manager's learning ability, career development, losing control of personal development, and losing the opportunity to learn from her/his own experience. Therefore, the following hypotheses are presented in the paper:

Hypothesis 2 – Multiple Regression

c. H0c: Perceived threat and career development (independent variables) are not necessary to influence a manager's use of AI (dependent variable).
d. H1d: Perceived threat and career development (independent variable) are necessary to influence a manager's use of AI (dependent variable).

2.6. Sample and Data Collection

The survey for the quantitative study was conducted in South Africa, Johannesburg. The sample consisted of people who live in the Mountains Estate. The people are managers who work across different sectors of the economy. These sectors are business and production across various organisations. It is important to note here that a fictitious name is given to the estate to protect the

identity and confidentiality of the participants of the study. The Mountains Estate contains 500 households. Each household contains a set of parents working in various industries. A total of 200 surveys were sent to managers working in different industries ranging from large to small organizations. Google Forms was the best option to collect data as all managers have access to accounts for Google. Therefore, it was convenient to fill in the survey in their personal capacity. The survey was completely voluntary and anonymous as mentioned in the disclaimer before completing the survey.

2.7. Developing Preliminary Scales of Behavioural Factors Influencing the Adoption of AI

This research measures behavioural factors influencing the adoption of AI in decision making depending on behavioural factors that display high common method variance, that is, high item characteristics effects. The research has a 9-item preliminary scale to measure the effectiveness of team decisions compared to AI.

Table 2. Constructs and Indicators of Survey

Construct	Indicator
Team and AI decisions	1. We involve all people who have a stake in or knowledge about the topic. 2. We listen to each person's thoughts and feelings about a topic to withstand the real issue(s). 3. All the options for a project or decision are put out on the table. 4. When we review our choices, we listen to everyone's negatives and positives on each option before deciding. 5. We monitor whether our decisions are working and promptly modify them as needed. 6. My team makes good quality decisions. 7. AI makes good quality decisions. 8. AI is likely to make bad decisions in the future. 9. The chances of AI making bad decisions are great in the present.
Perceived threat	1. My fear of exposure to AI's risks is high. 2. The extent of my worry about AI's risks is low. 3. The extent of my anxiety about potential loss due to AI's risks is high. The extent of my worry about AI's risks due to misuse is high.
Career development	1. AI-supported decision making has a positive impact on my learning ability. 2. AI-supported decision making has a positive impact on my career development. 3. I hesitate to use AI for fear of losing control of my personal development. 4. It scares me to think that I could lose the opportunity to learn from my own experience using AI-supported decision-making

Perceived AI threats influence employee behaviour to avoid the threats or the AI itself. It is evident through history that machines have replaced human efforts most especially in industrial work. The research has a 4-item preliminary scale to measure the level of threat AI poses to managers.

Career development concern was measured using four self-developed indicators based on prior studies with respect to the impact of AI-supported decision making on a manager's learning ability,

career development, losing control of personal development, and losing the opportunity to learn from her/his own experience. Table 2 summarises the constructs and indicators.

3. Results and Discussion

The responses were analysed using SPSS software from IBM. The analysis and discussion are presented below.

3.1. Hypothesis 1

The results for hypothesis 1 were tabulated below which draws the comparison between the quality of team decisions and the quality of AI decisions. The parameters that were used for the comparison include the following: mean, standard deviation, skewness, standard error of skewness, kurtosis and standard error of kurtosis.

Table 3. Comparison Between AI Decision Making and Team Decision Making

	Quality of Team Decisions	Quality of AI Decisions
Mean	74.95	59.29
Standard Deviation	20.067	26.425
Skewness	-.684	-.574
Std. Error of Skewness	.172	.172
Kurtosis	-.094	-.245
Std. Error of Kurtosis	.342	.342

Overall, table 3 indicates that managers rated team decisions higher on average than those decisions that were made by AI. In total, the mean of the quality of team decisions was rated to be 74.95% and the mean of the quality of AI decisions was rated to be 59.29%.

The standard deviation is used to assess how far individual points in a dataset are dispersed from the mean. In other words, whether there is a high volatility or risk between the indicators (accuracy). In this instance the standard deviation for both quality of team decisions and AI decisions where low or close to the mean (high accuracy of data). The skewness of team decisions was found to be -.68, indicating that the distribution is negatively skewed. The skewness of AI decisions was found to be -.57, indicating that the distribution is negatively skewed. In this instance, a negative skew represents that the average is below most of the data. The skewness explains in this example that there is only a small number of managers that do not experience high quality decisions from team decisions and AI decisions.

The kurtosis of team decisions was found to be -.09 indicating that the distribution is normal univariate. It is considered acceptable. The kurtosis of AI decisions was found to be -.24 indicating that distribution is normal univariate. It is also considered acceptable. The kurtosis explains how a manager might experience extreme fluctuations with the quality of decisions from teams and AI. In this instance the normal univariate explains that the high quality decisions is the norm in the workplace however more reliance is given to team decisions.

Therefore, in the study, H1b is an acceptable hypothesis. Team decisions are preferred over AI decisions.

3.2. Hypothesis 2

The results for hypothesis 2 are based on the following tables: multiple regression of perceived threat and career development on managers' use of AI, ANOVA model of perceived threat and career development on managers' use of AI and coefficient model of perceived threat and career development on managers' use of AI. Multiple regression was used to understand the relationship between multiple predictor variables (career development and perceived threat) and the response variable (managers' use of AI).

Table 3. Multiple Regression of Preceived Threat and Career Development on Managers' use of AI

R	R Square	Adjusted R Square	Std. Error of the estimate	Change Statistics				
				R Square change	F Change	Df 1	Df 2	Sig. F change
.744	.604	.590	1.403	.060	6.263	2	197	.002

Table 4. Anova Model of Perceived Threat and Career Development on Manager's Use of AI

ANOVA				
	Sum of Squares	Mean Square	F	Sig.
Regression	24.664	12.332	6.263	.002
Residual	387.931	1.969		

Table 5. Coeffiecient Model of Perceived Threat and Career Development on Manager's Use of AI

	Unstandardised Coefficients		Standardised Coefficients	T	Sig.	95% Confidence Interval for B	
	B	Std. Error	Beta			Lower	Upper
Constant	.696	.732		.950	.004	-.748	2.139
Perceived Threat	.254	.127	.174	1.989	.004	.002	.505
Career Development	.430	.122	.309	3.532	.001	.190	.670

In table 3, "R" column represents the multiple correlation coefficient. R is used the measure the quality of the prediction of the dependent variable. In this case it is .744 which indicates a good level of prediction. The "R square" column referred to as the coefficient of determination describes the proportion of variance in the dependent variable that can be explained by the independent variables. In this instance, the adoption of AI can be explained by .604 of the threat of AI and career development. The adjusted "R square" column represents the accuracy of the data and here it is .590.

Table 4 tests whether the overall regression model is a good fit for the data. Table 6 shows that the independent variables statistically predict the dependent variable. The overall regression was statistically significant r^2= .604, F (2.197) = 6.263 P = .002

Table 5 tests the significance of each independent variable. If P<.05 then the independent variables are statistically significant. The unstandardized coefficient indicates how much the dependent variable

varies with an independent variable when all other independent variables are held constant. Perceived threats had a statistically significant contribution to the outcome of a manager's use of AI which is .004. Personal development had a statistically significant contribution to the outcome of a manager's use of AI which is .001. As the perceived threat index increased by 1 unit of change, then there would be a .254 change (increase) in a manager's use of AI. For 1 full standard deviation that is seen in the perceived threat of AI, there is an increase in managers' use of AI by .174 standard deviations. In other words, if managers perceive AI as a threat to replacing their jobs, they are more likely to learn skills related to AI to prevent job loss. As the career development index increased by 1 unit of change, then there would be a .430 change (increase) in a manager's use of AI. For 1 full standard deviation that is seen in career development with AI, there is an increase in a manager's use of AI by .309 standard deviations. In other words, if managers perceive that AI will contribute to their career development, they are more likely to adopt using AI in their work and skills development.

Multiple linear regression was used to predict if the perceived threat of AI and personal development of AI significantly predicted the dependent variable which is the managers' use of AI. The fitted regression model was the managers' use of AI = .254 + .430

Therefore, the paper accepts hypothesis H1d. Perceived threat and career development (independent variable) are necessary to influence a manager's use of AI (dependent variable).

4. Contribution to Research and Limitations

Much literature is devoted to rewards and compensation as a form of motivating employees and retention strategies. The research here presents evidence that building AI skills can help to develop employees' careers which is also another form of motivation to stay with their organisation. The research also contributes to the existing literature on AI, showing that while managers are motivated by AI, they would not put their full trust into fully autonomous decision making. It supports existing research suggesting that AI works best as a decision-making tool when working in conjunction with human expertise.

The results from the paper reflect the views of managers from primarily the business and production sectors. Therefore, the results are expressed for only these two sectors. Future research would need to be conducted in other sectors to determine the impact on individuals' careers. In addition, due to budget constraints, the entire population in Johannesburg could not be studied. The practical implication of this research is that the individuals in the study come from diverse backgrounds and thus may have differing views that may have a small bias or preference towards their responses. Therefore, it may not be relevant to organisations or environments which are characterised by homogeneity of groups of people and social practices.

5. Conclusion

In the framework of our research, we developed a research portal that is meant to support research work applied in the meat industry, specifically pertaining to planned modern quality control and tracing systems and to the publication of the knowledge base connected with the topic. (Figure 1). (The paragraph style: Text – Paragraph)

The paper highlights some important findings that organisations, leaders and economies need to take into consideration. First, the degree to which governments and businesses can manage the AI-human interface is what the paper believes will ultimately decide the scope and pace of AI use in decision making (European Commission, 2024). It will be critical to be able to reduce the impact of human biases in the process and make appropriate use of AI input when making strategic decisions. Second, the incorporation of AI in decision making has sparked apprehensions about workforce impact and job displacement. Third, full employment could be reached if workers who are disrupted can find new jobs within a year, but in a more likely scenario, growth trends would differ. With middle- and low-skilled labour demands declining in more developed economies and semi-skilled

work opportunities increasing in developing countries, the income gap could also widen (Bjørnåvold & Coles, 2007).

Fourth, while AI interactions with economies and systems are complex, the principal means by which AI is likely to have a direct effect on employed individuals are the replacement of human workers, combinations of AI-enabled devices, systems and intelligent robots, and augmentation of human performance at work. The fifth is the degree to which AI will substitute humans as an input into the factor of production. Finally, governments need to address both the conceptual issues raised by AI as well as the practical effects that the technology is having on people's lives and means of subsistence. For governments, the fundamental balancing act is to foster conditions that facilitate AI growth and development while also reducing the hazards that AI poses. Policymakers should consider if and when it is appropriate to trust machines to make judgments; whether the values that are inherent in decision making align with societal norms and values; and how to deal with problems like biased datasets and outputs (Shiohira, 2021).

In summary, the paper identifies the potential impacts of AI on economies and individuals' careers. It was identified in the paper that the introduction of AI would result in the complete takeover of humans' jobs. However, a more likely scenario in future is that AI would work in conjunction with humans to make decisions. Therefore, higher demand for learning and development initiatives would inform the strategic budgeting process to help employees adopt the use of AI in their jobs, all the while committing to lifelong learning.

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