Gordon Institute
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Employee appraisal of artificial intelligence and intention to leave: Moderation by perceived organisational support via normative commitment

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Abstract

Implementing artificial intelligence in the workplace is becoming imperative for organisations to stay competitive. The event of AI introduction can serve as both a stressor due to perceived job insecurity or a challenge when an employee perceives he possesses sufficient resources to cope with the new technology. Employee appraisal of AI is related to his knowledge of the technology, the perception of operational and cognitive capabilities, and adverse outcomes of AI. The formed affective and cognitive appraisal has an association with the employee intention to use organisational AI or leave the company implementing it. The purpose of the study is to employ the model of employee appraisal of AI and understand if moderation by perceived organisational support and commitment to organisation exists.

216 respondents among skilled workers and different levels of management across South African industries have been surveyed. SmartPLS 4.0 algorithm was used for structural equation modelling. The study found the employee appraisal model to have good explanatory and predictive power. In addition, perceived organisational support had a full-moderation effect on the relationship between the employee attitudes to AI and intention to leave the organisation implementing AI, via mediation of employee normative commitment to organisation. The model also holds true for employees whose companies are in different stages of AI implementation, with the least embeddedness exhibited by those experiencing the uncertainty of the initial stages of AI implementation. The study findings allowed an insight into the factors of AI appraisal by employees and contain some recommendations for managers to prepare for the shift to AI-augmented workplace.

Keywords

Cognitive appraisal theory, artificial intelligence, employee appraisal of artificial intelligence, perceived organisational support, commitment to the organisation

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Yelena van der Grijp

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30 October 2022

List of abbreviations and acronyms

AI	Artificial intelligence
AO	Anticipated adverse outcomes of AI
AOjob	Anticipated adverse outcomes of AI: job-related
AOhum	Anticipated adverse outcomes of AI: humanity-related
AVE	Average variance extracted
BRlea	Behavioral response to leave the company
BRuse	Behavioral response to use organisational AI
CB-SEM	Covariance-based structural equation modelling
CC	Perceived cognitive capabilities of AI
CCcxt	Perceived cognitive capabilities of AI: context understanding
CClog	Perceived cognitive capabilities of AI: logic transparency
CClng	Perceived cognitive capabilities of AI: natural language understanding
CO	Commitment to organisation
COaff	Commitment to organisation: affective
COcnt	Commitment to organisation: continuance
COnrm	Commitment to organisation: normative
CR	Composite reliability
EA	Employee attitudes to AI
EAaff	Employee affective attitude to AI
EAcog	Employee cognitive attitude to AI
EAAIM	Employee appraisal of AI model
EK	Employee subjective knowledge of AI
HOC	Higher-order construct
HPWP	High performance work practices
HTMT	Heterotrait-monotrait
IAAAM	Integrated AI acceptance-avoidance model
LM	Linear regression model
LOC	Lower-order construct
MAE	Mean absolute error
OC	Perceived operational capabilities of AI
OCflx	Perceived operational capabilities of AI: flexibility
OCint	Perceived operational capabilities of AIL integrability
OCrel	Perceived operational capabilities of AI: reliability

PCA	Principal component analysis
PLS	Partial Least Squares
PLS-SEM	Partial Least Squares structural equation modelling
POS	Perceived organisational support
RMSE	Root mean square error
SEM	Structural equation modelling
VIF	Variance inflation factor

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1 RESEARCH PROBLEM AND PURPOSE

1.1 Background for the research problem

Business leaders who are trying to keep their companies competitive can no longer afford to ignore artificial intelligence (AI). To date, there has been extensive literature published on the benefits of employing AI for automating and augmenting organisational activities and decision-making processes (Borges, Laurindo, Spínola, Gonçalves & Mattos, 2021; Chiu, Zhu & Corbett, 2021), ranging from better performance on financial and operations indicators, to better valuations of the stock market (McAfee & Bryniolfsson, 2012). Companies are pushed to stay competitive and employ effective methods of production and client service. Due to considerable cost–benefit on usage of AI in organisations, the continuation of human workforce in some roles becomes questionable (Brougham & Haar, 2018).

A number of authors predicted a shift in capitalism from being labour and financial capital driven to knowledge and information driven accompanied by a decline in physical jobs (Drucker, 1993; Nam, 2019). Frey and Osborne (2017) emphasised a trend towards polarisation of the labour market with employment growth in cognitive and manual jobs, the latter due to a higher degree of physical adaptability and flexibility required (Autor & Dorn, 2013). Meanwhile, routine jobs are expected to shrink (Frey & Osborne, 2017). In addition, AI has been advancing into non-routine domains which rely on the availability of big data (Brynjolfsson & McAfee, 2011; Frey & Osborne, 2017). Although human labour has prevailed due to the adaptability of humans in acquiring new skills (Goldin & Katz, 2009), this will become more challenging with the advancement of technology into cognitive domains and jobs associated with high dexterity and enhanced senses, with higher than human reliability of output (Brynjolfsson & McAfee, 2011; Frey & Osborne, 2017). Workers in susceptible tasks are likely to move to non-susceptible tasks, such as those that require creativity and social intelligence (Frey & Osborne, 2017).

Implementation of AI in workplace is creating hope and fear among executives, managers, experts and labour force alike. Office workers, business analysts and operations employees foresee a reduction in the workforce with AI taking over their jobs, with the trend reversing with higher managerial ranking (Ransbotham, Gerbert, Reeves, Kiron & Spira, 2018). This creates concerns to management and human resource specialists to address the challenges of low morale, job embeddedness and staff reskilling.

1.2 Business need

The landscape described above poses demands on organisations to have a proactive approach in identifying the problematic areas of the business and preparing their employees for the re-skilling (Frey & Osborne, 2017). While regulatory institutions and political movements may be directed to slow down the adoption of AI, this process is inevitable, due to an observed increase in wage levels relative to the cost of capital which makes automation highly attractive for companies (Frey & Osborne, 2017). The progress in adopting AI in business processes across different industries and continents has been uneven, where the companies which were born digital have a considerable advantage over those that have inherited legacy information and technology systems (McAfee & Bryniolfsson, 2012).

To add complexity to the issue, employees have different levels of knowledge of AI, as well as different cognitive and emotional attitudes to AI, which can lead to diverse behavioural outcomes towards a company's decision to adopt AI solutions (Chiu et al., 2021). These behaviours include increased job embeddedness or elevated intention to leave the company (Chiu et al., 2021). In addition, threats of the introduction of AI systems in the workplace can act as major stressors in perceived job insecurity (Nam, 2019), and have consequences for organisational effectiveness, further leading to a threat of job loss and accelerated organisational decline (Greenhalgh & Rosenblatt, 1984).

Together, this variety of factors in employee perception can complicate the range of considerations a company needs to take cognisance of when intending to embark on AI implementation campaigns. A proactive approach to the employee appraisal of AI adoption is required (Nam, 2019; Chiu et al., 2021). Pioneering organisations emphasise the workforce implications and, while predicting an enormous business value from the implementation of AI, call for careful management of organisational change (Ransbotham et al., 2018).

1.3 Theoretical need

Findings of the research are aimed to provide empirical support for an employee appraisal of AI model and help to shed some light on how to prepare for the shift with the right balance of new skills acquisition and career re-skilling to transition the existing labour force accordingly while enabling employers, employees, and policymakers (Brougham & Haar, 2018).

A need for studies to better understand employee appraisal process of AI in the workplace and the varying, often extreme and paradoxical, attitudes of the employees to AI has been highlighted by a number of authors (Lichtenthaler, 2020; Chiu et al., 2021). To the best of the author's knowledge, at the moment of writing the current report, there has been only one study applying the cognitive appraisal theory for pre-adoptive AI appraisal by employees in Taiwan (Chiu et al., 2021). The model was designed to reflect negative and positive employee appraisal factors and reflect affective and cognitive attitudes of the employees toward AI. The final behavioral outcomes of the appraisal process in the model have been the intent to use the organisational AI or to leave the company. Demographic moderating factors were tested in the preceding study, as well as the employee level of knowledge of AI. The research by Chiu et al. (2021), motivated for the expansion of the study into jurisdictions other than Taiwan to allow model generalisability and refinement of boundary conditions. In addition, the authors did not obtain support for all the hypothesised relationships in the model, possibly attributable to a strong collectivistic culture in Taiwan (Hofstede, 1980; Chiu et al., 2021; National culture comparison tool, n.d.).

The current study attempted to address some of the identified gaps, such as obtaining further empirical support for the model, applying it to a jurisdiction with different cultural dimensions, and testing moderating effect of perceived organisational support mediated via commitment to organisation (CO) on the paths linking employee attitudes - behavioral outcomes, which has not been attempted before.

In addition, the preceding study argued that the appraisal of AI among employees of the companies in pre-adoptive stage of AI implementation differs dramatically from those where AI has been operationalised. The authors confined their study to a population comprised of staff of the companies in pre-adoptive stage of AI appraisal. The current research attempted to understand if the employee appraisal model of AI holds across employees of firms at different stages of AI implementation, with the latter moderating the relationships in the model.

1.4 Scope and context

The general purpose of the study is to empirically test the employee cognitive appraisal theory (Lazarus & Folkman, 1984) as applied via an employee appraisal of AI model (Chiu et al., 2021) referred to as EAAIM further in the text, for brevity, and understand if the relationships between the employees' attitudes to AI and their intent to use the system or leave the company is moderated by other variables. Some of the tested moderation variables are supposed to be under direct control of the company, such as the perceived organisational support. The others are, arguably, not, or at least, have complex antecedents. This category includes the employee organisational commitment and stage of AI implementation in the company. The moderation analysis has been conducted to gain insights into possible implications for managers and human resource practitioners to mitigate for possible adverse effects of the AI perception on the employee behavioral outcomes. The cognitive appraisal theory proposed by Lazarus and Folkman (1984) serves as the basis of the study. Its implementation via a model of AI apparaisal, EAAIM, (Chiu et al., 2021) has been tested, with the same hypotheses posed. Indirect moderating relationships have been added to the model to understand influence of other factors on the important paths. Extant research on perceived organisational support and commitment to organisation constructs has been investigated to allow meaningful application.

The current study addresses some of the gaps identified in the preceding investigation by Chiu et al. (2021). The scope of the study was somewhat broader than in the mentioned previous research, investigating the employee appraisal of AI at different stages of AI implementation in the company, while the previous research focused on pre-adoptive stage of AI implementation. No restriction has been made to a particular stage of AI adoption in the organisation to allow new insights into moderating effect of the stage of AI implementation on behavioral outcomes.

The data collection took place over a span of two months. The research was not limited to any particular organisation, sector or discipline. The majority of the respondents (72%) came from mining and energy, as well as manufacturing and production sectors. It has mainly focused on employees in South African companies, with 94% of the respondents comprising this group. It is believed the study is generalisable across companies in different stages of AI implementation in South African context.

1.5 Research objectives

The objectives of the study are aimed at obtaining empirical support on the factors of cognitive and affective attitudes of employees towards AI, and the effect thereof on behavioural responses (BR), such as intention to use AI (BRuse) and intention to leave the company (BRlea). In addition, a moderating effect of perceived organisational support (POS) on the relationship between employee cognitive and affective attitudes and the behavioural outcomes was tested, via a mediating role of employee commitment to the organisation. To summarise, the main objectives of the study are:

1. To gain support for the cognitive appraisal theory (Lazarus & Folkman, 1984) as applied via EAAIM to AI implementation in a company (Chiu et al., 2021), and evaluate the effect of AI appraisal on behaviour outcomes;
2. To understand the moderating effect of POS on the relationship between appraisals and behaviour outcomes;
3. To ascertain if the commitment to the organisation has a mediating effect on the moderated relationship described in item 3 between employee appraisal and behaviour outcomes;
4. To test for a moderating effect of a stage of AI implementation in a company on the relationship between employee appraisal and behaviour outcomes.

The pages below proceed by explaining the main theories used in the research. They are followed by an overview of the methodology and research design, after which analysis of findings and key conclusions are outlined.

1.6 Conclusion

There have been increasing pressures on businesses to accelerate adoption of AI. Employees' knowledge and attitudes towards AI differ considerably, and can lead to undesirable outcomes for the company, if not managed properly. In order to stay proactive, organisations need to recognise the challenges associated with workforce adoption of AI and prepare for the shift, paying attention to re-skilling programs to enable their employees (Frey & Osborne, 2017). Companies getting it right are having a leapfrog advantage over the incumbents. That is related to the fact that large number of work force has considerable organisational knowledge, while at the same time are not native with the AI technology. While younger technology-savvy generation can adapt faster, it is not the case with older workers. To successfully transition in incumbent companies would means to understand the workforce, identify the desired state, problem areas in transforming the workforce, and steps to get there.

The following chapter will provide literature review on the constructs employed in the study and the state of the problem in the AI adoption among the workforces.

2 LITERATURE REVIEW

2.1 Introduction

The current chapter presents an overview of the extant literature on the theory behind the research. The chapter is structured as follows. An overview of the cognitive appraisal theory is presented, followed by the insights into the current debate on the cognitive appraisal theory, and a further focus on AI appraisal. Extant literature review is given to allow extending the cognitive appraisal theory as applied to the employee appraisal of AI model and include moderation by perceived organisational support via mediating commitment to organisation. A short literature overview covering these aspects concludes the chapter.

2.2 Cognitive appraisal theory overview

The research made use of the cognitive appraisal theory, also termed a transactional model of stress and coping. Formalised by Lazarus and Folkman in 1984, the theory posits that when faced with a new or challenging situation, an individual undergoes a process of appraisal followed by a coping mechanism which leads to different behavioural responses. The appraisal process has cognitive and affective aspects (Lazarus & Folkman, 1984).

2.2.1 Cognitive appraisal

Cognitive appraisal implies a process of evaluating an event intellectually with regards to its relevance to well-being. Stressful encounters have the potential to be considered threats of challenges. A threat carries a cognitive component of personal harm or loss. It triggers negative emotions such as fear, anxiety, and anger. Challenge appraisals are underlain by a sense of control over the situation, contain a cognitive component of potential for growth, and are associated with positive emotions such as enthusiasm, exhilaration, and excitement. The same event can be considered a threat and a challenge simultaneously. Both call for coping efforts (Lazarus & Folkman, 1984).

As an encounter unfolds, the appraisal can shift along the threat-challenge continuum depending on the changes in the environment, availability of personal resources, and modification of coping strategies. The adaptation has important implications, as people who perceive a new encounter as a challenge rather than a threat are more likely to be more confident and less emotionally overwhelmed, better utilise the available resources, have higher morale, and, possibly, be less prone to a severe physiological stress response. Coping refers to cognitive and behavioural efforts aimed at managing those external or internal strains which are perceived to exceed the personal resources. A coping response is a function of the resources at the individual’s disposal as well as personal and environmental constraints (Lazarus & Folkman, 1984).

Among the important personal factors that influence cognitive appraisal are commitments and beliefs, as they underlie the choices, carry a motivational quality, and can give rise to emotions. The deeper a person's commitment to an endangered aspect of his life, the greater the potential for it to be considered a threat or a challenge, and the greater the motivation toward ameliorative action. In addition, the less ambiguity a person experiences about a particular situation, the higher the likelihood that his/her emotions and coping processes will be affected by the appraisals of being in control. As such, the commitments and beliefs work interdependently with situation factors, determining the gravity of the threat or challenge perception (Lazarus & Folkman, 1984).

2.2.2 Affective appraisal

The cognitive appraisal theory (Lazarus & Folkman, 1984), despite the deceptiveness of its name, makes reference to emotional appraisal process being conjoined to the cognition. Cognitive appraisal is a necessary antecedent of emotional appraisal, as intellectual processing of information allows to identify what is relevant and important for well-being. An emotional response is thus dependent on the evaluation of meaning stemming from the cognitive processing of a situation. Affective appraisal can occur early in the evaluation process due to the fact that intellectual evaluation is often based on partial rather than full information about a phenomenon.

Chiu et al. (2021) indicated that extant literature of AI and technology appraisal had mainly focused on cognitive attitudes of employee appraisal of AI in isolation, rather than considering both cognitive and affective attitudes, which potentially could lead to an incomplete understanding of the appraisal process. They mitigated it by introducing the affective appraisal element in their model explicitly.

2.3 The current debate on the cognitive appraisal theory

The cognitive appraisal theory (Lazarus & Folkman, 1984) has received significant attention in academia with a number of studies investigating the effect of personal and organisational characteristics on the relationship between challenge and hindrance stressors, with the two stressor types having distinctly divergent effects on individuals (Cavanaugh, Boswell, Roehling & Boudreau, 2000). The authors suggested that individuals' divergent appraisal is a result of internal and external factors, for instance, workload and role ambiguity. However, a meta-analysis of 72 articles using Cavanaugh et al. (2000) model suggested that it had some methodological issues pointing toward unreliable generalisability, and subsequent academic failures to replicate its results (Mazzola & Disselhorst, 2019). While the extant research did demonstrate some relationships between challenge and hindrance stressors with some organisational variables, among them employee engagement and performance, the association with other important variables, such as physical and mental health or counterproductive work behaviours, was found to be negative for both types of stressors. In addition, the potential negative consequences of challenge stressors were found to outweigh any positive ones. As such, the authors posited that research on organisational stress should diverge from the popular challenge-hindrance model either in favor of the original cognitive appraisal-based approach (Lazarus & Folkman, 1984), or other established models (Mazzola & Disselhorst, 2019). The emphasis should be on the specific appraisal of stressors by employees, such as implementation of AI, and avoidance of any a-priori assumptions on the inherent hindering or challenging character of the stressor under study. To concur with the finding, the current study employed the appraisal-based approach in its original form (Lazarus & Folkman, 1984), focusing on a specific employee appraisal of AI adoption.

2.4 The current debate on the AI appraisal

An attempt to introduce the current debate on the employee appraisal of AI described below helps to position the research in the context of the recent related developments in academic space and is by no means exhaustive.

2.4.1 Employee appraisal of AI model (EAAIM) for pre-adoptive stages of AI implementation

The cognitive appraisal theory (Lazarus & Folkman, 1984) has been adapted for the employee appraisal of AI, by Chiu et al. (2021), via EAAIM, to get empirical support from 363 Taiwanese employees for a pre-adoptive appraisal of AI. Due to the perceived stressfulness of the situation when their companies intend to implement AI, the employees undergo a cognitive appraisal process, antecedents of which are their knowledge and familiarity with AI, perceived cognitive (CC) and operational (OC) capabilities of AI, and anticipated adverse outcomes of AI (AO). The pre-adoptive employee appraisals of AI (EA), via mediation by cognitive (EAcog) and affective (EAaff) employee attitudes, lead to behavioural responses, such as intention to use organisational AI (BRuse) or to leave the company (BRlea). Ultimately, such responses either augment or impair the organisational ability to implement AI solutions. The study showed that the way an employee perceives the operational and cognitive capabilities of AI is positively related to his/her cognitive and affective attitudes toward AI (with low attitudes values signifying negative attitudes, and high values – positive). At the same time, employee concerns with regards to AI adoption showed a negative association with affective attitude only. The study pointed toward the importance of considering a wide range of practical implications for organisational preparedness when rolling out AI solutions (Chiu et al., 2021).

2.4.2 Employee appraisal of AI through responsible AI signals

Wang, Chen, Xiong & Wang (2021) studied a possibility of accelerated AI adoption in healthcare sector and proposed a concept of so-called key responsible-AI signals which comprised justice, autonomy, explainability, beneficence and non-maleficence. They showed empirically that these signals positively correlated with the attitudes of employees toward AI, their satisfaction with this technology, and the intent to use it via increased employee engagement with AI. At the same time, techno-overload was considered as a stressor in employee appraisal of AI, due to a frequent perception of additional workload. It was found to weaken the strength of the association between responsible AI justice and employee attitude to AI, satisfaction, and intentions to use AI, undermining the AI justice positive effects. The authors emphasised importance of understanding the AI adoption from an employee perspective, and a need to build systems which focus on AI explainability, justice, autonomy, beneficence, and non-maleficence, facilitated by appropriate training interventions (Wang et al., 2021).

2.4.3 AI usage by clients in service industry

A significant body of research has been dedicated to AI appraisal within organisations and amongst the client base. Gursoy, Chi, Lu and Nunkoo (2019) utilised the cognitive appraisal theory to propose a three-stage AI devise use acceptance model to substantiate customer willingness to accept AI in the service industry. The appraisal took a form of a multistage process. It started with the evaluation of the relevance and importance of the AI application. The main antecedents of the appraisal as emphasised by the authors were hedonic motivation, social influence, and anthropomorphism. They were followed by the evaluation of the perceived performance of the technology and effort expectancy during usage. The cognitive appraisal led to an emotional appraisal of the specific usability of the AI device. The resulting outcome, namely, willingness or objection to the usage of AI, was the product of the cognitive and emotional appraisal processes. Positive emotions of a client toward the usage of AI reduced the effect of the negative appraisal (Gursoy et al., 2019).

2.4.4 Usage of AI by managers for decision-making

Cao, Duan, Edwards and Dwideli (2021) proposed an integrated AI acceptance-avoidance model (IAAAM) to investigate the attitudes and behavioural intentions of managers towards AI application in decision-making. The model was based on two theories: the technology threat avoidance theory (Liang & Xue, 2009) and the unified theory of acceptance and use of technology (Venkatesh, Morris, Davis & Davis, 2003). Unlike most literature on information technology appraisal which adopts either an acceptance or avoidance paradigm, the IAAAM considers both, positive factors affecting managers' appraisal of AI for decision-making, as well as negative ones. The model emphasises the importance of establishing favourable facilitating conditions to lighten managers' concerns, due to performance and effort expectancy. It motivates to consider both, the positive and the negative side of using AI for organisational decision-making. Some practical considerations are to ensure appropriate technological infrastructures as well as proper training and support to elevate personal concerns that contribute to the "dark side" of AI (Cao et al., 2021; Dwivedi et al., 2021). A similar approach has been adopted in the current research, establishing employee attitudes to AI and their relation to affective and cognitive appraisal, on a positive/negative evaluation scale.

2.4.5 Employee attitudes to AI and job insecurity

Brougham and Haar (2018) introduced the concept of STARA which stands for smart technology, artificial intelligence, robotics, and algorithms. For the purpose of the current discussion, it can be summarised under a notion of AI. They tested the effect of the employee awareness of STARA on their perception of it as a threat to their career and job. The study indicated that a greater awareness of the implications of STARA adoption was negatively related to career satisfaction and job embeddedness, while positively related to turnover intentions, depression, and cynicism. This finding was indicative of a start of a new era of a conditional commitment to a company and a multidirectional career and could be exciting for some employees as an opportunity for growth (Brougham & Haar, 2018), while stressful for others. At the same time, the findings showed that awareness of STARA was not significantly correlated with job insecurity. The authors indicated a gap in the knowledge with regards to moderating or controlling variables associated with job insecurity. The current study attempted to address this gap in the context of the chosen model, as applied to employee attitude – behavioral outcomes relationships.

2.4.6 Perceived sustainability and insecurity of job

Nam (2019) hypothesised that perceived job insecurity is a result of the employee's perspective on the socio-economic situation, the immediate work environment, and the organisational specifics. It reflects an unintentional change in one's continuity of employment. Job insecurity is regarded as a stressor and has been found to have negative long- and short-term consequences for the organisation and its employees. The author explored a connection between the perceived job insecurity and the owner's attitudes toward technology adoption and found that the perception was highly correlated with the individual's technology usage and long-term beliefs regarding the job. The possibility of unemployment is correlated with perceived job insecurity, however, there is no causation link. Due to the fact that the population experiencing job insecurity considerably outstrips the population who will actually lose their jobs due to the advancement of AI, this is a serious concern, as it influences organisational outcomes via reduced job satisfaction, performance, and commitment. The author suggested adopting a proactive approach to delineating the affected workforce and rolling out technology-driven solutions in organisations to ensure a smooth transition toward the Fourth Industrial Revolution. Referring to Keim, Landis, Pierce & Earnest (2014), the author emphasised that employers should participate in active in-advance communication about upcoming plans and changes, involve employees in the process of the new job design, transform the organisational psychological contracts with their employees, and enforce new ones by improved communication (Nam, 2019). As a suggestion for future research, the author suggested examining an ensemble of different factors affecting the perceived job insecurity, such as psychological factors, technology usage, and social factors. Rather than testing job insecurity as a focal point, the current research places an emphasis on the behavioral outcomes stemming from AI appraisal, and the effect of employee commitment to organisation.

2.4.7 Employee attitude to AI and its moderation

Similar to the model adopted in the current research, Lichtenthaler (2020) emphasised different employee attitudes towards AI, ranging from fascination and openness to reluctance and fear, frequently experienced by the same individuals. The negative attitudes are mostly a product of science fiction conditioning and a fear of job loss, according to the author. A challenge in most companies considering AI adoption would be to actively manage the employee attitudes shifting them from negative to neutral and positive. In practice, the wide range of employee attitudes would require designing suitable interventions tailored to the context. This will gain increasing importance due to a growing competitive relevance as negative appraisals can have detrimental consequences on firm performance. The author posited that as the augmentation of human intelligence by AI becomes an important factor of competitive advantage in the future, organisations will know no alternative but to address negative attitudes among their workforce.

2.4.8 Employee appraisal of AI and psychological contracts

The implication of AI appraisal by employees from a perspective of psychological contracts has been considered by Braganza, Chen, Canhoto and Sap (2021). While employee engagement in workplace is positively influenced by existence of psychological contracts, adoption of AI in a company has been found to have a negative effect on employee engagement, irrespective whether the employee has a transactional or relational contract. The authors proposed a third type of a psychological contract, termed “alienation”. This type is associated with ad hoc arrangements, with limited human interaction, and sporadic instalments of work, all facilitated by algorithm-driven decision-making void of human interaction. They authors suggested a need for trade-offs to plan for AI implementation support, to avoid emergence of alienation psychological contracts in a company. The argument found a reflection in the current study by inferring a need for increased organisational support to moderate the effect of the employee attitudes to AI and the intention to use AI or leave the company.

2.5 Moderation of AI appraisal

As the objective of the research is to provide pragmatic insights to organisations and human resource practitioners on the proactive approach to mitigate negative AI appraisal in employees resulting in unwanted behavioural responses, a number of moderating variables have been considered to be included in the model. Initially, among them were characteristics of leadership, perceived organisational support, and commitment to organisation.

Literature research has been conducted to understand viability of using leadership style as a moderator in the model. Two leadership styles were investigated, namely, transformational leadership and servant leadership. It has been found, however, that while being important in leadership research, there have been concerns over the construct and content validity for both transformational and servant leadership styles, with empirical results being of limited value and academic calls to return to nascent and intermediary theory phases (Andersen, 2018; Siangchokyoo, Klinger & Campion, 2020). Hence, an idea of using leadership style as a moderator in employee AI appraisal has been abandoned.

2.5.1 Organisational support

Perceived organisational support represents employees’ belief that their company cares for their well-being, listens to their voices and values their work (Arasanmi & Krishna, 2019). Previous empirical studies indicated that perceived organisational support factors, such as recognition of employee’s contribution, caring about employee’s wellbeing, and consideration of personal values in decision-making, were an important moderator between AI awareness and turnover intention. Employees who feel appreciated and supported by their companies tend to respond with increased commitment, loyalty, dedication, and psychological attachment to the company (Brougham & Haar, 2018; Li, Bonn & Haobin, 2019). Hence, the perceived organisational support construct was chosen to be included in the model for moderation.

2.5.2 Commitment to the organisation

Numerous definitions and measurement models for organisational commitment have been proposed in the last three decades (Ahmad, 2018). A conceptualisation by O'Reilly et al. (1991) suggested three dimensions: 1) compliance, reflecting the acceptance of authority in exchange for benefits, 2) identification, as a consequence of the employee's desire to be affiliated with the company, and 3) internationalisation, stemming from the congruence in values between the employee and the company. Meyer, Allen and Smith (1993) reviewed O'Reilly et al. (1991) classification approach suggesting three forms of organisational commitment: affective (COaff), continuance (COcnt), and normative (COnrm). The affective component of the commitment was a combination of the previously suggested identification and internationalisation dimensions, the compliance was re-branded as continuance commitment, and the normative commitment was freshly introduced (Meyer et al., 1993; Ahmad, 2018).

Employees who have a strong affective commitment stay in the company because they have emotional attachment to the firm and their experience within the company is in line with their hopes and satisfies their basic needs. The affective commitment has been argued to correlate stronger than the continuance and normative dimensions with levels of productivity in the workplace as well as absenteeism and turnover intention, and as such, is seen as the most important to nurture in a company (Ahmad, 2018). Those with pronounced continuance commitment are motivated to stay out of self-interest. They evaluate comparable opportunities outside the organisation in terms of costs of leaving and benefits of remaining with the company and stay if the latter overweights the former. It is prompted by perceived sacrifice of leaving due to accumulated benefits and a lack of alternative options. A perceived sacrifice has a stronger relationship with the turnover intention than does the perception of alternatives by the employee. Finally, normative commitments are strong as a result of socialisation, emphasising the value of loyalty to the organisation or reciprocal benefits obliging the person to stay (Meyer et al., 1993; Ahmad, 2018). The reciprocity suggests that an employee experiences a normative obligation to repay to the organisation in exchange for being treated above his/her normal expectations (Ahmad, 2018).

Empirical support of the mediating role of CO on the relationship between POS and turnover intention has been found by Arasanmi and Krishna (2019). Nasurdin, Ling and Khan (2018) established a similar mediating effect, however, the independent variable they tested was high-performance work processes (HPWP) such as performance appraisal, compensation, and employment security. There also has been a suggestion towards an existence of indirect effect of the organisational support on the employee attitudes and behavior, via employee commitment to the organisation (Ahmad, 2018). Albalawi, Naugton, Elayan and Sleimi (2019) who studied non-management employees in Jordanian small and medium enterprises found a significant mediating effect of organisational commitment on the association between POS and turnover intention.

The commitment to organisation, however, can be complicated by dissimilarities between generations. A study by Glazer, Mahoney & Randall (2019) investigated differences between GenX and Millennials in organisational commitment. The GenX group are considered to be born between mid-1960s and early 1980s, while the Millennials between early 1980s and mid-1990s. The differences between generations are determined by economic, political and technological differences existing in their adolescent years which had a direct effect on the groups' beliefs, norms, identities and values. In turn, these generational differences in culture had a spill-over effect on their expectations of the ideal workplace, management style and their behavior as employees (Becton, Walker & Jones-Farmer, 2014; Glazer et al., 2019). The authors found lower levels of continuance commitment in the Millennials' group, while there were no differences observed among the two groups in normative and affective commitment. A prior meta-analysis by Costanza, Badger, Fraser, Severt and Gade (2012), on the other hand, revealed that there was a less pronounced continuance commitment and greater affective and normative commitment among GenX than Millennials.

2.5.3 Stage of AI implementation

Chiu et al. (2021) focused their study of the employee appraisal of AI on pre-adoptive stage of AI implementation, when organisations still contemplate the need for a technological solution and have to operate in a context of limited cues. The authors argued that at this stage, factors which were considered for technology post-adoption did not apply. Some of such factors mentioned by other researchers were expectancy of high level of performance, anticipation of required effort, and social influence for the use of the AI under consideration. In the post-adoptive appraisal, when the technology is known, the employee can consider its immediate impacts at work, ease of use, usefulness, effort expectancy, organisational readiness, and can accurately estimate whether he/she possesses resources to adopt the technology. As a result of this assessment, the employee might adopt one of the four behavioral outcomes: deviant, reluctant, compliant and engaged (Bhattacherjee, Davis, Connolly & Hikmet, 2018).

Due to lack of such information in pre-adoptive stage, a general preconceived idea about AI capabilities and the effect thereof on the workplace is formed. Together with availability of personal resources, these evaluations determine the employee cognitive and affective attitudes, which, in consequence, lead to certain behavioral responses, such as increased job embeddedness and intent to use the technology (Chiu et al., 2021). The current research rather than isolating the populations of the employees by the stage of AI implementation in their companies, presumes that the overall model holds across the companies in different stage of AI adoption, and rather attempts at gaining insights on a moderating nature of the stage of AI implementation in the company.

2.6 Conclusion

The current chapter gave a short overview of the extant literature in the space of employee appraisal of AI, from the roots of the classical theory development to the recent debate on the AI appraisal in the workplace. The moderation of the AI appraisal has been related to the research of organisational support and commitment to organisation. The table below summarises the literature review. The following chapter will introduce the reader to the research hypotheses.

Table 1. Summary of main reviewed literature on AI appraisal

Concept	***Publication***
Cognitive appraisal of AI	
Cognitive appraisal theory	Lazarus & Folkman, 1984
Relationship between challenge and hindrance factors	Cavanaugh et al., 2000
Suggested divergence from a rigid challenge-hindrance to specific appraisal of stressors	Mazzola & Disselhorst, 2019
Employee appraisal of AI	
The model of the pre-adoptive appraisal of AI, EAAIM, using the cognitive appraisal theory	Chiu et al., 2021
Employee appraisal of AI via responsible AI signals	Wang et al., 2021
Post-adoptive appraisal and behavioral outcomes	Bhattacherjee et al., 2018
Positive effect of emotional AI appraisal on cognitive appraisal	Gursoy et al., 2019
Technology acceptance and avoidance ("dark" side) in employee attitudes to technology	Cao et al., 2021
Negative correlation between awareness of AI implications and career satisfaction and job embeddedness	Brougham & Haar, 2018
Correlation between the employee level of technology usage and long-term beliefs regarding the job with the employee perception of job insecurity	Nam, 2019
Employee positive and negative attitudes to AI necessitating company interventions	Lichtenthaler, 2020 Ransbotham et al., 2018
Employee appraisal of AI and psychological contracts	Braganza et al., 2021
Perceived organisational support and commitment to organisation	
Perceived organisational support moderation of the employee behavioral responses to AI	Brougham & Haar, 2018; Li et al., 2019
Organisational commitment	Meyer, Allen and Smith, 1993; Ahmad, 2018
Mediating role of commitment to organisation on POS - turnover intention	Arasanmi & Krishna, 2019
Mediating role of commitment to organisation on HPWP - turnover intention	Nasurdin et al., 2018

3 RESEARCH HYPOTHESES

3.1 Introduction

The research model used in the study is comprised of the elements of the cognitive appraisal theory (Lazarus & Folkman, 1984) as adapted by Chiu et al. (2021) via EAAIM. In addition, the moderation by POS (Eisenberger & Huntington, 1986) via the mediator variable CO (Meyer et al., 1993) were added to the model. The tested model is shown in Figure 1. The elements of EAAIM are contained within the rectangle, the added elements are shown outside the rectangle in Figure 1. The abbreviations representing different measurement items can be found in Appendix 1, the abbreviations of construct names are given in Figure 1.

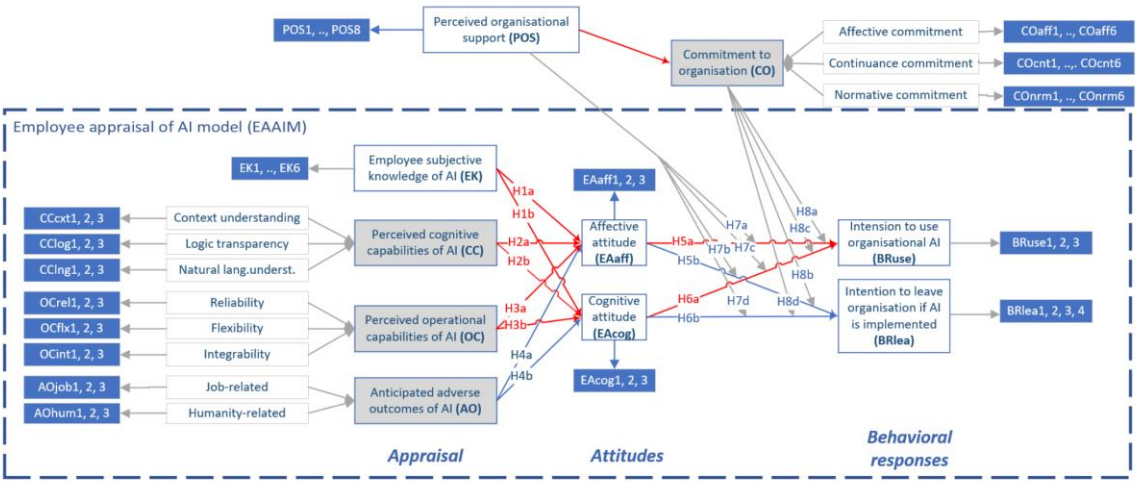

Figure 1. Diagram of the research model proposed for the study.
The elements of EAAIM are contained within the rectangle.
The items have been coloured as follows: with blue background - the measurement items, transparent with grey outline – lower order constructs, transparent with blue outline – single-order constructs, grey with blue outline – higher-order constructs. The endogenous model paths are shown in red (for positive correlation) and blue (for negative correlation)

The tested model comprised of four groups of latent variables related to: 1) the appraisal of AI, 2) employee cognitive and affective attitudes; 3) two behavioral responses, intention to use the organisational AI and intention to leave the company where AI is adopted; 4) moderating effect of perceived organisational support and employee commitment to organisation.

While Chiu et al. (2021) used EAAIM in application to AI pre-adoptive appraisal, the current study approached it without confining the sample to a pre-adoptive stage of implementation, proposing that the model holds across the different stages of implementation. Chiu et al. (2021) isolated the pre-adoptive stage of AI implementation in their study arguing that employee appraisal of technology at this stage differs from appraisal in other stages of AI implementation. The post-hoc analysis of the current study explored the stage of AI implementation as a categorical moderating variable. This relationship was not framed as a hypothesis and is not shown in Figure 1.

The section below provides specifics of interaction between the different groups and introduces the hypotheses tested in the study.

3.2 Model direct relationships

3.2.1 Appraisal and employee attitude constructs association

The appraisal group of constructs in the model has been comprised of four elements: a single-order construct of employee subjective knowledge of AI, and three higher-order constructs (HOC) of perceived cognitive and organisational capabilities of AI as well as anticipated adverse outcomes of AI.

3.2.1.1 Association of employee subjective knowledge of AI and employee attitudes towards AI

The constructs of the individuals' initial appraisal are the resources they have (Lazarus & Folkman, 1984) and their perception of the technology (Chiu et al., 2021). Knowledge serves as one of the main resources available to an employee. There are two types of knowledge: objective knowledge, reflective of what we know as measured by a test, and subjective knowledge, representative of what we think we know (Carlson, Vincent, Hardesty & Bearden, 2008). The absolute difference between the two reflects the miscalibration by an individual (Carlson et al., 2008). Due to the difficulty of measuring objective knowledge of AI (Chiu et al., 2021), subjective knowledge was measured in the study instead. As found by Carlson et al. (2008) via a meta-analysis of consumers' objective and subjective knowledge, they are closely related. The relationship between the employee subjective knowledge and objective knowledge has been found to vary across previous studies, from non-significant to significant (Carlson et al., 2008). The author proposed that when the user's experiences do not facilitate the acquisition of objective knowledge, the user's objective knowledge is limited, hence correlations between the objective and subjective knowledge can be low. Klerck and Sweeney (2007) indicated that such situations can arise in areas that yield themselves poorly to communication of knowledge, as can be when dealing with scientific knowledge, where people can be over- or underconfident in what they know (Chiu et al., 2021). Further when referring to the construct of employee subjective knowledge in the study, for brevity, it has been termed employee knowledge (EK).

Knowledge has been shown to have a significant effect in the appraisal process. Negative appraisal of AI can take place due to a lack of associated knowledge about AI, as shown by Abdullah and Fakieh (2020) in consumer goods industry. Chiu et al. (2021) could not establish a direct association between an employee knowledge of AI and his/her attitudes towards AI. They, however, demonstrated an indirect moderating impact of knowledge on cognitive and affective attitudes and employee behavioral responses. Although an employee might have a high expectation of adverse outcomes of AI, when this is combined with a high level of knowledge of AI, he/she will not have as negative cognitive attitudes, as an employee with low level of AI knowledge. With higher knowledge there will be better understanding of technology capabilities and limitations resulting in reassessment of adverse consequences (Chiu et al., 2021). The following hypotheses were suggested:

H1a. Employee subjective knowledge of AI is positively associated with affective attitude toward AI.

H1b. Employee subjective knowledge of AI is positively associated with cognitive attitude toward AI.

3.2.1.2 Association of perceived cognitive and operational capabilities of AI and employee attitudes towards AI

The perceived cognitive capabilities of AI included context understanding (CCcxt), logic transparency (CClog) and natural language processing (CClng) (Chiu et al., 2021; Srinivasan, 2016), while the perceived operational capabilities included reliability (OCrel), flexibility (OCflx) and integrability (OCint) of AI into different enterprise systems (Chiu et al., 2021; Nelson, Todd & Wixom, 2005).

Similar to employee subjective knowledge of AI, the stronger the employee's perceptions that AI has strong operational and cognitive capacities, the stronger are the positive affective attitudes of the employee. This is due to a belief that implementing AI will potentially reduce repetitive and dull work and augment decision-making (Chiu et al., 2021). Having positive affective attitudes towards technology is important for perceiving a technology as a challenge rather than a threat and developing internal resources and coping strategies (Chiu et al., 2021; Lazarus & Folkman, 1984).

Chiu et al. (2021) found that both, operational and cognitive capabilities of AI as perceived by an employee had positive correlation with affective and cognitive attitudes of the employee towards AI during pre-adoptive stage of AI implementation. The following hypotheses were suggested irrespective of the stage of AI implementation in the company:

H2a. Cognitive capabilities of AI as perceived by an employee have a positive association with employee affective attitude toward AI.

H2b. Cognitive capabilities of AI as perceived by an employee have a positive association with employee cognitive attitude toward AI.

H3a. Operational capabilities of AI as perceived by an employee have a positive association with affective attitude toward AI.

H3b. Operational capabilities of AI as perceived by an employee have a positive association with cognitive attitude toward AI.

3.2.1.3 Association of anticipated adverse outcomes of AI and employee attitudes towards AI

The HOC of anticipated adverse outcomes of AI is proposed to comprise of two lower-order constructs (LOC): job-related (AOjob) and humanity-related (AOhum) outcomes (Chiu et al., 2021). The main job-related adverse outcomes are job insecurity (Nam, 2019), substitution (Lichtenthaler, 2020), anticipated change in the job content, and trends toward labour market polarisation with middle-income routine jobs experiencing declining demand while high-income cognitive and low-income manual jobs trending towards growing employment demands (Frey & Osborne, 2017). There are situations when employees exhibit limited openness to AI, preferring interaction with humans based on empathy and emotional intelligence (Lichtenthaler, 2020). Humanity-related adverse outcomes are largely prompted by science fiction depicting future scenarios where robots take over the world in future (Lichtenthaler, 2020).

Presence of anticipated adverse outcomes of AI among employees forms an important consideration for organisations as they can lead to reduced job embeddedness and diminished workforce motivation. In the previous study by Chiu et al. (2021), it has been found that anticipated adverse outcomes of AI were negatively correlated with the affective attitudes only. However, no significant relationship has been established between the anticipated adverse outcomes and cognitive attitudes. The authors attributed this lack of correlation to individual differences and complexity of human nature when an individual can hold controversial cognitive attitudes towards AI - an appreciation of the benefits it brings and concerns about its negative impacts. In the current study, the following hypotheses were suggested, regardless of the stage of AI implementation in the company:

H4a. Anticipated adverse outcomes of AI as perceived by an employee have a negative association with his/her affective attitude toward AI.

H4b. Anticipated adverse outcomes of AI as perceived by an employee have a negative association with his/her cognitive attitude toward AI

3.2.2 Employee attitudes toward AI and behavioural outcomes association

Two behavioral attitudes have been considered in the model, intention to use enterprise AI and intention to leave the organisation. Empirical research by different authors on the correlation between attitudes and behaviour has not shown consistent results, suggesting the presence of confounding factors (Chiu et al., 2021), and a finding that cognitive rather than affective attitudes hold a strong correlation with the employee intention to use the system (Yang & Yoo, 2004). At the same time, the effect on the employee behaviour is stronger when the purpose of the system and the type of the attitude are congruent. For example, a hedonic system strengthens the relationship between the affection and the intention to use the system, and a utilitarian system amplifies the association between cognitive attitudes and the intention to use it (Chiu et al., 2021).

Positive emotions contributing to a sense of achievement, perceived benefits of AI or excitement about human-like intelligence observed in AI increase the employees' commitment and motivation to use it (Chiu et al., 2021; Ding, 2018; Huang, Rust & Maksimovic, 2019). On the other hand, negative emotions and stress factors associated with usage of a specific technology can be hindrances in technology adoption (Chiu et al., 2021).

It has been found that both, affective and cognitive attitudes are positively associated with the employee intention to use organisational AI (Chiu et al., 2021). With the regards to the employee's intent to leave the organisation, only affective attitude was found to exhibit a significant negative correlation. The cognitive attitude shown to have no impact on the employee embeddedness, as such yielding an unexpected result to the authors.

The hypotheses relating the employee attitudes towards organisational AI and behavioral responses in the current study, irrespective of the stage of AI implementation, are framed as follows:

H5a. Affective attitude toward AI is positively associated with intention to use enterprise AI.

H5b. Affective attitude toward AI is negatively associated with intention to leave the organisation if AI is implemented.

H6a. Cognitive attitude toward AI is positively associated with intention to use enterprise AI.

H6b. Cognitive attitude toward AI is negatively associated with intention to leave the organisation if AI is implemented.

The summary of the hypotheses testing results for EAAIM as established by Chiu et al. (2021) is shown in Table 2.

Table 2. Summary of hypotheses testing in a previous study employing EAAIM part of the proposed study model (Chiu et al., 2021)

Hypothesis ID	***Hypothesis***	***Previous research***
1a	Employee knowledge of AI is positively associated with affective attitude toward AI	Not supported
1b	Employee knowledge of AI is positively associated with cognitive attitude toward AI	Not supported
2a	Perceived cognitive capabilities of AI have a positive association with affective attitude toward AI	Supported
2b	Perceived cognitive capabilities of AI have a positive association with cognitive attitude toward AI.	Supported
3a	Perceived operational capabilities of AI have a positive association with affective attitude toward AI	Supported
3b	Perceived operational capabilities of AI have a positive association with cognitive attitude toward AI	Supported
4a	Anticipated adverse outcomes of AI have a negative association with affective attitude toward AI	Supported
4b	Anticipated adverse outcomes of AI have a negative association with cognitive attitude toward AI	Not supported
5a	Affective attitude toward AI is positively associated with intention to use enterprise AI	Supported
5b	Affective attitude toward AI is negatively associated with intention to leave the organisation if AI is implemented	Supported
6a	Cognitive attitude toward AI is positively associated with intention to use enterprise AI	Supported
6b	Cognitive attitude toward AI is negatively associated with intention to leave the organisation if AI is implemented	Not supported

3.3 Model indirect effects

3.3.1 Perceived organisational support effect on the employee attitudes to AI - behavioural outcomes paths

EAAIM in pre-adoptive stages of AI implementation (Chiu et al., 2021) has been extended in the current research to incorporate two indirect effects: a moderating effect of perceived organisational support on the behavioral outcomes, and the same effect but mediated by commitment to organisation.

A number of previous studies showed empirical support for the association between POS, CO and behavioral outcomes. Arasanmi and Krishna (2019) investigated the role of POS in a form of employer branding techniques for attracting and retaining employees. They have found that there was a positive association between organisational support and employee retention, which was mediated by organisational commitment. A study by Nasurdin et al. (2018) conducted in hospital nurses in Malaysia undertook to explore a relationship between HPWP and turnover intention with a mediating role of CO. The HPWP included concepts of performance appraisal, compensation and levels of job security. The authors reported no direct effect of HPWP on turnover intention, but rather a mediating effect, expressed mostly for performance appraisal and compensation.

The following hypotheses were proposed to test for the moderating effect of POS (Brougham & Haar, 2018; Li et al., 2019) on the behavioural outcomes:

H7a. POS affects the relationship between affective attitude and intention to use AI such that the relationship is strengthened with perceived high level of organisational support.

H7b. POS affects the relationship between affective attitude and intention to leave the company such that the relationship is weakened with perceived high level of organisational support.

H7c. POS affects the relationship between cognitive attitude and intention to use AI such that the relationship is strengthened with perceived high level of organisational support.

H7d. POS affects the relationship between cognitive attitude and intention to leave the company such that the relationship is weakened with perceived high level of organisational support.

3.3.2 Commitment to the organisation effect on the employee attitudes to AI - behavioural outcomes paths

Further to the above, based on the literature review (Arasanmi & Krishna, 2019; Nasurdin et al., 2018), it was proposed that CO had a mediating effect on the moderating relationship of POS on attitudes and employee behavioural responses associations. The following hypotheses have been tested:

H8a. CO mediates the moderating relationship of POS on affective attitude - intention to use AI.

H8b. CO mediates the moderating relationship of POS on affective attitude - intention to leave the organisation.

H8c. CO mediates the moderating relationship of POS on cognitive attitude - intention to use AI.

H8d. CO mediates the moderating relationship of POS on cognitive attitude - intention to leave the organisation.

3.4 Conclusion

The chapter provided the research model and an overview of the research hypotheses. The chapter to follow will explore the research methodology and means to test the hypotheses.

4 RESEARCH METHODOLOGY

4.1 Introduction

The following chapter gives an overview of the methodology employed for investigating the empirical support for the model used in the study. Details of the quantitate study are provided with specific insights into the philosophy, purpose and different methodological choices behind the chosen approach. Limitations of the study are also reflected.

4.2 Research paradigm

The positivist research philosophy on knowledge development adopted in the study relies on verification of a-priori hypotheses which are often stated in quantitative forms. They rely on deriving relationships between explanatory factors and their outcomes, with an ultimate goal of explaining, predicting and controlling the phenomenon under investigation. They make use of a hypothetico-deductive model of theory description, hypothesis testing, operationalisation and experimentation (Park, Konge & Artino, 2020). There are a number of philosophical foundations of the positivism paradigm. The ontological premise relates to the nature of reality. It suggests that there is a single identifiable and measurable reality that can be explained and predicted by using a causal framework. The causal inferences rely on temporal precedence of events, association between them, and absence of confounding factors which would affect the outcome within the identified space (Park et al., 2020). The epistemology concerns the nature of knowledge. In order for the scientific knowledge to represent true reality, a complete separation between the researcher and respondents must be ensured. This is achieved through dualism or separation between the two groups of stakeholders which leads to reduced bias and achieves objectivity in the study (Park et al., 2020). The axiological premise reflects values of staying objective in the research process. It dismisses any subjective values of the researcher and of the participants by ensuring the researcher stays objective during data collection (Park et al., 2020).

The positivist approach relying on hypothetico-deductive modelling has been considered appropriate for the study. The theory of the cognitive appraisal has been shown to have empirical support as adopted to AI pre-adoptive appraisal process by employees. There is a need to further confirm and refine the theory by striving for good explanatory and predictive power of a model. Developing the theory of cognitive appraisal of AI is believed to facilitate an employee-centred approach of organisations towards improving employee attitude and minimising negative outcomes for companies faced with the inevitable advance of the AI.

4.3 Research design

The research design refers to procedures used by the researcher to achieve the objectives of the study, starting from formulation of hypotheses to data analysis and reporting. In the positivism research paradigm, two approaches exist, experimental and non-experimental. During the experimental process, new hypotheses can be posed, and theories refined. The non-experimental research does not involve experimentation during the data collection process (Asenahabi, 2019). Quantitative methods produce strong scientific evidence, which is important in positivism research philosophy, where numerical data and its analysis is the source of the knowledge generated in the study. When applied to social sciences it has the purpose of providing a generalisable output (Park et al., 2020).

The quantitative approach is considered to be appropriate for the current study due to a number of reasons. The main one is that the cognitive appraisal theory has been extensively used in social sciences and found empirical support as applied to employee appraisal of technology (Cavanaugh et al., 2000; Mazzola & Disselhorst, 2019; Gursoy et al., 2019; Chiu et al., 2021). It allows rigorous statistical testing to subject the posed hypotheses to the appropriate criticism (Cortina, 2020). A quantitative approach was applied by Chiu et al. (2021) previously, to test EAAIM in the pre-adoptive stage of AI implementation. The current research builds on the previous work and allows gaining more empirical support in the understanding of the problem.

The approach adopts a deductive causal design of theory development. Deductive research is aimed to collect data to test theoretical propositions and hypotheses to an existing theory and if relevant, suggest modifications to it. The causal design allows testing for causality of relationships between variables (Saunders & Lewis, 2018). The deductive causal approach has been considered suitable as EAAIM is quite complex, involving many variables connected by direct and indirect relationships, and a way to understand a phenomenon of such complexity is by breaking it up into smaller chunks addressable by focused hypotheses.

Data was collected following a survey strategy with a structured questionnaire relying on a mono methodological choice. Survey is employed to collect data in a form of multi-choice answers to questions, each representing a different variable in the model. The responses are gathered from a sample group to infer the attitudes and characteristics of a population at the given moment in time (Saunders & Lewis, 2018; Asenahabi, 2019). The survey approach was deemed appropriate for the current study as: 1) the model contains a large number of variables, connected by complex direct and indirect relationships, and requires rigorous statistical investigation with very specific hypotheses (Asenahabi, 2019), 2) the survey method has been employed before by testing the hypothesised relationships for both, EAAIM (Chiu et al., 2021) and the moderating relationships from POS and CO, 3) quality measurement instruments existed from the relevant previous studies, and 4) the survey approach allows collection of structured responses via Likert scale instruments, which yield themselves well to versatile statistical analysis.

A cross-sectional time horizon was adopted over a longitudinal one mainly due to time constraints for the completion of the research. Cross-sectional studies allow to carry out the observations at a given point in time gaining a snapshot insight into a phenomenon, while longitudinal studies are instrumental to understand temporal trends (Asenahabi, 2019).

4.4 Population and sample

Classical probability-based approach to sampling surveys defines a sampling frame related to the attributes of the reference population, follows an efficient sampling plan and uses propensity weights from the sampling plan to allow generalisation to the reference population. The increasing challenges in this approach are high cost of data collection, timeliness, achieving randomisation and high response rate, no missing data, null attrition, and ethical considerations, which make this goal often unattainable (Keiding & Louis, 2016; Lenau et al., 2021). Non-probability sampling approaches, on the other hand, do not focus on an accurate representation of a population of interest where equal chance is ensured for different categories of the population (Saunders & Lewis, 2018). They are associated with lower costs, time requirements, and higher response rate, and are gaining momentum. They, however, bring about problems of transportability of inferences to the population (Keiding & Louis, 2016). There is a current debate over representation issues in both probability and non-probability sampling (Keiding & Louis, 2016; Lenau et al., 2021).

A snowballing non-probability sampling technique was adopted in the research. It relies on seeding the initial round of responses in the population and asking the participants to propagate further to similar individuals. The technique is perceived to yield successful results due to its convenience, flexibility, and networking qualities, and has been reported to be suitable for reaching a mainstream audience (Saunders & Lewis, 2018).

The target population comprised the universe of individuals with a broad spectrum of knowledge of AI, representing skilled workers and different levels of management across South African industries. The population had to be sufficiently comfortable with technology to be able to access email, social media sites, or WhatsApp groups and answer the online questionnaire. Arguably, the respondents had to possess a degree of persistence, which might have been motivated by a belief in the importance of the study, in order to fill a survey questionnaire comprised of 82 questions. No specific companies were targeted to allow generalisability of the findings. Another reason for it was that the study contained questions relating to perceived organisational support and commitment to organisation which were expected to provide biased responses if the participants were aware that the survey was facilitated by their company. Hence a decision was made to conduct a survey via author's personal network emphasising anonymity and purely academic nature of the research.

The population was seeded among the professional network of the author. This network comprised mostly of specialists, and middle, senior and top managers, across different industries in South Africa. The network was represented by students completing Master's degree in Business Administration at the Gordon Institute of Business Science, and professionals in mining industry in South Africa, which in their absolute majority fell into the category of specialists and managers of different levels. A significant number of baseline demographic questions allowed to gain attribute information to stratify the sample during the statistical analysis.

The seed was initiated by distributing a link to a structured questionnaire via emails, posting it on the author's LinkedIn professional profile and WhatsApp study groups. The respondents were asked to self-complete and distribute it further electronically. The unit of analysis was at the level of an individual, the decision driven by the research objectives to empirically test the appraisal model of an employee towards AI.

A sample of 223 responses was collected, which, after cleaning, resulted in 216 usable responses (see Section 5.2 below for details). A number of considerations are important when deciding on a sample size appropriate for quantitative research. Among them are the theoretised size of the population, research constraints, desired accuracy in the estimation of the model parameters, presence of research questions relying on desired statistical power to test effect size, and heuristics associated with general rules or norms (Lakens, 2021). The previous study testing EAAIM by Chiu et al. (2021) made use of 363 responses which the authors deemed sufficient to find significance in most tested hypotheses, while utilising the SmartPLS algorithm for hypotheses testing. The current study also made use of the SmartPLS approach (see Section 4.7.1 for details). The justification of the number of samples for the current research was based on the inverse square root method (Kock & Hadaya, 2018). This method can be considered rather conservative if small path coefficients are used (Hair, Hult, Ringle, Sarstedt, Danks & Ray, 2021). It stipulates that the probability that the ratio of a path coefficient to its standard error must be greater than the critical value of a test statistic for a desired significance level. For a significance level of 5% used in the model testing, a conservative approach was used. The previous study showed the smallest β path coefficients (Chiu et al., 2021) to be 0.1-0.2. Both of these coefficient's values were substituted into the equation (1) below to obtain the minimum number of samples (N) for the p-value of 0.05 (Kock & Hadaya, 2018; Hair et al., 2021):

$$\hat{N} > \left(\frac{2.486}{|\beta|_{min}}\right)^2 \tag{1}$$

This approach produced values ranging between 55 and 220 for the minimum number of samples, qualifying the collected number of responses as adequate.

4.5 Measurement instrument

The survey questionnaires were adapted from literature (see Appendix 1). The quality of the constructs has been tested with prior empirical research and found to be appropriate for the study (Chiu et al., 2021). Most of the questionnaires used a 5-point Likert scale with 1 signifying "strongly disagree" and 5 – "strongly agree". Reverse coding was used where appropriate.

For employee subjective knowledge of AI, a 5-item scale originally proposed and tested in consumer knowledge by Flynn and Goldsmith (1999) and adopted by Chiu et al. (2021) in application to testing employee AI subjective knowledge, has been used in the study (Appendix 1.2). The employee subjective knowledge was found to correlate highly with the objective knowledge, albeit the correlation can be weaker for complex phenomenon. It also reflects the employee's confidence about the subject (Chiu et al., 2021). In the preceding research, the scale showed to be consistent, with high reliability and validity (Flynn & Goldsmith, 1999).

The employee perceptions of cognitive and operational capabilities of AI were measured as higher-order constructs, each containing three dimensions. The measurement scale for cognitive capabilities contained nine items describing context understanding, logic transparency and natural language understanding developed by Chiu et al. (2021) who based it on Srinivasan (2016). The operational capabilities instrument measured perceived AI reliability, flexibility and integrability (Chiu et al., 2021; Nelson et al., 2005).

The measurement instrument for anticipated adverse outcomes of AI (Appendix 1.3) consisted of six items describing job-related (Chiu et al., 2021) and humanity-related constructs (Chiu et al., 2021; Jiang, Muhanna & Klein, 2000). The affective and cognitive attitudes measurements have been adopted from Chiu et al. (2021) and Yang and Yoo (2004) as LOCs of AO construct. Two behavioral attitudes have been considered, as in the originally proposed EAAIM (Appendix 1.4), namely, intention to use enterprise AI (Teo, 2011; Chiu et al., 2021) and intention to leave the organisation (Shore & Martin, 1989; Chiu et al., 2021).

In order to test the moderating effect of the perceived organisational support in the model, a measurement instrument consisting of eight items (Appendix 1.5) as originally suggested by Eisenberger, Huntington, Hutchison and Sowa (1986) was adopted. The HOC of commitment to organisation was captured via three LOCs of affective, continuance and normative commitment (Meyer et al., 1993). The three dimensions were found to be distinguishable and highly reliable with Cronbach's alphas between 0.72 and 0.81 (Meyer et al., 1993).

4.6 Data collection

The survey was set up using Google Forms. The data was gathered by means of a self-administered questionnaire using a snowballing technique. Three approaches to generate the seeding were used: posting the link to the survey on the author's LinkedIn professional profile, sharing it on the author's study groups, and approaching contacts in the professional network. The communication on each of the channels contained an introduction to the study, an invite to participation as well as a request to distribute the survey link further. No reward was offered. Anonymity was assured. The survey was open from the 18th of July to the 19th of September 2022.

Pre-testing was done by three individuals from the researcher's professional network with a different degree of understanding on AI and from different industries. The comments allowed to refine some questions, mostly from the demographics section. No major changes were done to the measurement instruments due to the fact that they had been statistically tested and confirmed suitable in measuring the different constructs by previous research. Most of the comments during the pre-testing were pointing out that some questions felt repetitive, however this was deemed appropriate and expected by the researcher as questions were designed to measure the majority of the constructs in the study reflectively.

4.7 Data analysis and interpretation approach

4.7.1 PLS-SEM algorithm

The initial part of data analysis involved descriptive statistics, such as count of responses, mean, median and standard deviation. The main part of the analysis comprised of structural equation modelling to test the plausibility of the model. Due to a large number of latent variables in the model, a preference was given to Partial Least Squares (PLS) structural equation modelling (SEM) regression, employing Smart PLS 4.0®. The statistical foundation of PLS-SEM was developed by Wold (1975). While finding some criticism and debate over its pros and cons, the method has been reported to become widely used in the recent research due to a number of advantages over covariance-based structural equation modelling (CB-SEM) tools. The latter considers the data covariance matrix, estimates model parameters by using the common variance and has a number of restrictive assumptions. Variance-based PLS-SEM uses total variance in parameter estimation of partial model structures, by combining principal component analysis (PCA) and ordinary least squares regressions (Hair et al., 2019b).

One of the advantages of the method is robust statistical performance in estimating complex models containing multiple constructs and structural paths. No assumptions on the underlying distributions need to be made. PLS is robust with small sample size, capable of achieving convergence even at 100 samples. It does so by separate treatment of the measurement and structural model relationships with ordinary least square regressions. However, representativity of the sample is still a must (Hair et al., 2019b).

The algorithm enables derivation of latent variable scores for further analyses. Another advantage over covariance-based SEM is a higher flexibility when defining the model, specifically when construct measurements are specified formatively, or when the path model is based on the LOCs jointly forming the HOCs (Hair et al., 2019b; Ringle, Sarstedt & Gudergan, 2018). A number of options are available in PLS to model the moderator variable influence, with a two-stage approach found to outperform in terms of statistical power and parameter recovery (Becker, Ringle & Sarstedt, 2018; Hair et al., 2019b). PLS aims at minimizing the bias and error variance. It provides causal-predictive SEM, satisfying both, the model explanatory power, pursued in academic research, and its predictive power, an objective for managerial applications (Hair et al., 2019a). Reported superior statistical power of PLS-SEM allows to better identify statistically significant relationships, important in theory development stage (Hair et al., 2019a). The advantages described above were the motivators for choosing PLS for the current study.

4.7.2 Quality control

Quality assurance and quality control enable the trustworthiness and reliability of the research. In quantitative studies, some of the aspects include sampling design decisions, sampling bias, error elimination during data manipulation, and quality of conclusions (Sanders & Lewis, 2018). Quality control was ensured in a number of steps, firstly, by conducting a pilot survey to test the clarity of the questionnaire. Efforts were made to minimise the sampling bias by targeting a sufficient sample size and ensuring participant anonymity and diligence in data cleaning (Sanders & Lewis, 2018). Detailed demographic data allowed to conduct post-hoc moderation analysis to ensure meaningful inferences. The data cleaning process consisted of checks for missing values. Calculation of standard deviation per response was done to ensure no automatic box-ticking took place.

The assessment of the PLS-SEM results comprised of the two main steps: measurement model followed by the structural model testing. The appropriateness of the approach to the model performance assessment was ensured by considering the types of the constructs: reflective or formative.

4.7.2.1 Types of constructs

The identification of the type of construct is important in measurement model assessment, as it affects the validation approach (Freeze & Raschke, 2007). When model contains formative constructs, PLS-SEM is preferred over CB-SEM (Hair et al., 2019b). In the proposed model, all the higher-order constructs (shown in grey in the Figure 2), such as perceived cognitive capabilities of AI, perceived operational capabilities of AI, anticipated adverse outcomes of AI and commitment to organisation are formative constructs. The lower-level constructs are reflective, except perceived organisational support. It is questionable if affective commitment to organisation is a formative construct, however for the purpose of this study it was assumed to be such. The HOCs in the model are reflective-formative. Figure 2 shows the model with the type of relationship displayed in green text next to the path arrows.

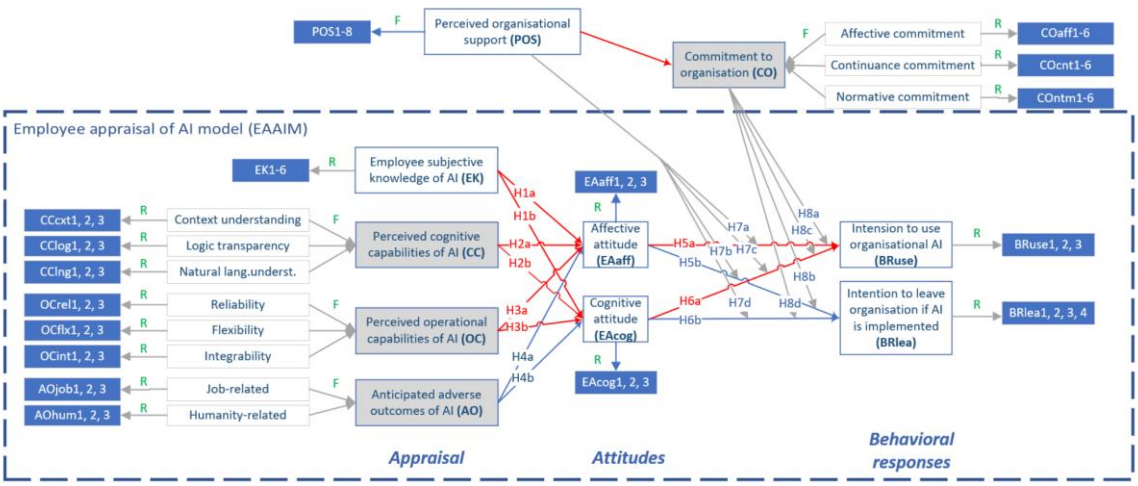

Figure 2. Diagram of the research model showing the type of constructs in the study.
The elements of the cognitive appraisal model are contained within the rectangle.
The items have been coloured as follows: with blue background - the measurement items, transparent with grey outline – lower order constructs, transparent with blue outline – single-order constructs, grey with blue outline – higher-order constructs. The endogenous model paths are shown in red (for positive correlation) and blue (for negative correlation). The green R and F letters denote reflective and formative constructs paths correspondingly

4.7.2.2 Measurement model assessment

The measurement model evaluation formed the first step in the model results assessment. A number of performance indicators were considered: indicator reliability, internal consistency reliability, convergent validity and discriminant validity. The initial step in assessing a reflective construct consisted in examination of the indicator loadings to establish the indicator reliability. Factor or indicator loadings reflect the strength of correlation between each measured item in the correlation matrix with the construct, with the range of possible values between -1 and +1 (Hair et al., 2019b). Researchers refer to different threshold values: 0.5 has been recommended to flag items of concern (Hair, Matthews, Matthews & Sarstedt, 2017), while 0.708 has been recommended as ideal (Hair et al., 2019b). In this case, 50% of the indicator variance is explained, providing acceptable reliability. However, the author suggested for removal only items with loadings below 0.4. Those between 0.4 and 0.708 should only be removed if it leads to an improvement in internal consistency, reliability or validity to become above a relevant threshold value (Hair et al., 2019b). The threshold of 0.5 was used to flag items for removal in the current study.

In the next step, internal consistency reliability was assessed. It reflects the degree of consistency and repeatability in the measurement instrument, via the degree to which items in the same construct have association with each other (Hair et al., 2019b). The commonly used approaches to testing the reliability, utilised in the current research, are Cronbach’s alpha and composite reliability (CR). In CR, construct indicators are weighted by factor loadings, resulting in higher values than Cronbach’s alpha. In calculating Cronbach’s alpha, the items are unweighted, setting it to be a less precise measure of reliability. Similar thresholds are targeted for the two parameters: values ranging between 0.7 and 0.9 are considered satisfactory to good in exploratory research, those between 0.6 and 0.7 - acceptable. Values exceeding 0.95 can be problematic indicating possible redundancy among the items or undesirable response patterns (Hair et al., 2019b). The true reliability of a construct sits between the two measurements (Hair et al., 2019b).

Convergent validity tests that the constructs that should be related, are, in fact, related (Hair et al., 2019b). The measures of a construct should covary considerably in order to be considered valid measures of the construct (Hair et al., 2019b). To estimate it, the average variance extracted (AVE) was calculated for each reflective construct. It was established by computing a mean value of squared loadings of all items in the construct. A minimum acceptable threshold of 0.5 was used, which implied that at least 50% of the variance of the items were explained by the construct (Hair et al., 2019b).

Discriminant or divergent validity, as the term suggests, tests the opposite to the convergent validity, namely, that the constructs which are not supposed to have a relationship, do not exhibit it, and are empirically different from the other constructs (Hair et al., 2019b). A number of measures exists. Fornell-Larcker criterion has been a traditionally used metric. It compares the AVE value to the squared inter-construct correlation for each construct, and with each other reflective construct in the model. The shared variance for all constructs in the models is expected to not exceed the AVE of a construct under consideration (Hair et al., 2019b). When indicator loadings of a construct are very similar, between 0.65 and 0.85, the Fornell-Larcker criterion has been found to underperform (Henseler, Ringle & Sarstedt, 2015; Hair et al., 2019b).

Another method of measuring discriminant validity is heterotrait-monotrait (HTMT) ratio. It represents a mean of item correlations across constructs relative to the geometric mean of the average correlations of items comprising each construct (Hair et al., 2019b). The maximum allowed threshold of 0.90 is acceptable in models with similar constructs, and 0.85 for models where conceptually the constructs are distinct (Henseler et al., 2015).

In presence of HOCs, in addition to evaluation criteria commonly applied in any PLS-SEM analysis, such as validity and reliability, two additional measurement model assessments need to be considered: 1) of the lower-level constructs, and 2) of the higher-order constructs to test the relationships between the HOCs and LOCs (Sarstedt, Hair, Cheah, Becker & Ringle, 2019). In evaluation of formative measurement models, Hair et al. (2019b) suggest testing convergent validity, collinearity, as well as statistical significance and relevance of the indicator weights.

A number of approaches have been suggested for assessing the quality of measurement models with HOCs. Among them are single stage approaches and two-stage approaches, comprising the embedded and the disjoint approaches. The two methods produce similar results (Sarstedt et al., 2019). The disjoint two-stage approach has been used in the study. As the name suggests, the method consists of two stages. In the first one, only the LOCs are preserved in the path model with direct links to all the constructs their HOCs are linked to as per the model theory. The output of this stage are the construct scores for the LOCs. In stage two, the LOCs with their indicators are removed from the model and replaced with the previously created scores. The single-order constructs are preserved with their measured indicators (Sarstedt et al., 2019).

The measurement model validation approach, implemented in this research, consisted of two stages. LOCs and single-order constructs were measured in stage one. The criteria included factor loadings, collinearity, reliability, convergent validity and discriminant validity. In the second stage, three tests were done for assessing the HOC, in which LOCs represent the indicators: 1) collinearity between indicators, 2) significance and relevance of outer weights and other loadings, and 3) convergent validity (Sarstedt et al., 2019; Hair et al., 2017). Collinearity in both stages was measured with the variance inflation factor (VIF). For formatively measured constructs, the ceiling of 5.0 was accepted. If exceeded, collinearity issues are present between the indicators (Hair et al., 2019b).

Testing of indicator weights significance and relevance in PLS is done using bootstrapping due to the fact that PLS-SEM is a non-parametric approach (Hair et al., 2019b). The absolute contribution of the item to the construct is established by considering the significance of the weight and its absolute value. If the weight and the loading are non-significant then the indicator is eliminated. If the loading is low but significant, the indicator can be deleted unless there is a strong support for keeping it (Hair et al., 2019b). In general, removal of indicators from formative models should be done with caution as they are not interchangeable and it can lead to reduced content validity of the model (Hair et al., 2019b).

4.7.2.3 Structural model assessment

The structural model was assessed upon satisfactory completion of the measurement model testing. With the use of the disjoint two-stage approach, the model was assessed on the basis of the second stage output, using the multi-items created in the first stage (Sarstedt et al., 2019). Collinearity was assessed prior to the testing of direct and indirect relationships significance and relevance. For determining the mediation type, a decision map suggested by Hair et al. (2019b) and shown in Figure 3 was used.

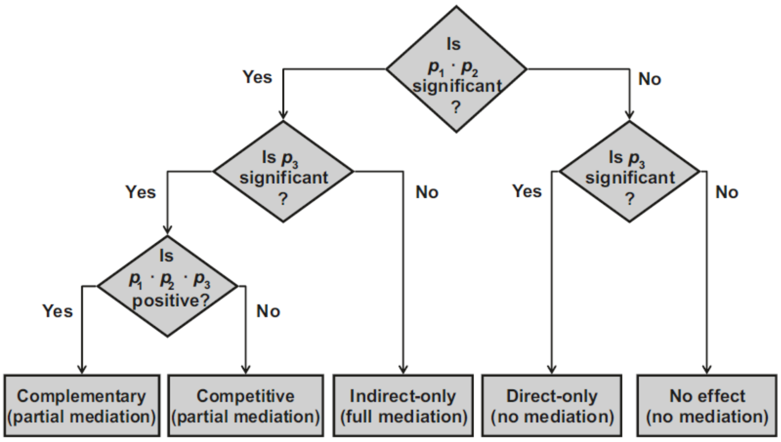

Figure 3. Decision map for determining the presence and type of mediation (Hair et al., 2021)

Explanatory power of the model

A number of methods exist to measure the model explanatory power. One of them is assessing the R^2 value for endogenous variables. It measures the variance explained by informing variables and represents the in-sample predictive power. It is higher with larger number of predictor constructs. The thresholds of 0.75, 0.50 and 0.25 refer to substantial, moderate and weak explanatory power correspondingly. These thresholds, however, should be considered in the context of the study – the more predictable the process the higher the values (Hair et al., 2019b).

The effect size metric, f^2, indicates how much the R^2 value changes with the removal of an exogenous construct. If the f^2 values are higher than the thresholds of 0.02, 0.15 and 0.35, the effect size is considered small, medium and large (Cohen, 1988; Hair et al., 2019b).

A combination of out-of-sample prediction and in-sample explanatory power is provided by the parameter Q^2. It is based on a blindfolding technique where points in data matrix are removed, their values are imputed with average values and the model parameters are estimated. The estimated model is then used to predict the removed data values, and the differences are estimated into Q^2 values. The values above 0.00, 0.25 and 0.50 are interpreted as having small, medium and large predictive levels (Hair et al., 2019b; Shmueli, Ray, Estrada & Shatla, 2016). All of the above-mentioned assessments were used in the study.

Predictive power of the model

Besides the Q^2 parameter described above, predictive power of the model was assessed using PLSpredict within SmartPLS software. The approach relies on k-fold cross-validation. The model estimation is performed using on a training sample. The predicted results are compared against a holdout sample subset of the dataset (Hair et al., 2019b). The assessment is done by $Q^2_{predict}$ criteria, followed by analysis of root mean square error (RMSE) or mean absolute error (MAE). The RMSE assigns a greater weight to larger errors via squaring, and is useful when large errors are undesirable, as in business research applications. It is also preferred when the distribution of the prediction error is symmetric (Hair et al., 2019b). The decision on the predictive power of the model when using either metric relies on comparison to the naïve linear regression model (LM) threshold. If all indicators have lower RMSE or MAE value in comparison the LM benchmark, the model is said to have high predictive power. If none of the indicators are lower than the benchmark, then it has no predictive power. A 50% proportion is used as a decision point to decide whether the model has medium or low predictive power (Shmueli et al., 2019; Hair et al., 2019b).

4.7.2.4 Bias

Some of the most significant reliability threats are subject error and subject bias (Saunders & Lewis, 2018). The first was mitigated by structuring the questionnaire in a clear way and conducting a pilot testing. There is, however, always a danger of subject bias.

4.8 Limitations

While the population is believed to be defined sufficiently well, the main limitation of the study relates to the sampling approach. The population represented skilled workers and different levels of management in South African companies. In comparison to the previous study using EAAIM (Chiu et al., 2021), the population included employees from companies at different stages of AI adoption, arguing that the stage of adoption could be incorporated as a moderating variable into the model. The adopted sampling approach brings into question the external validity which represents the degree to which the findings within the sample can be transferred to the population (Keiding & Louis, 2016). Snowball sampling has been criticised for lack of generalisability, external validity, and representativeness. Since the seed is dependent on the researcher’s personal resources and contacts, it is subject to a selection bias (Parker, Scott & Geddes, 2020), and the sample is characterised for being not random. The traditional gold standard in quantitative research has been defined as probabilistic sampling with rigour applied to identification of the sampling frame, however, there has also been a trend in support of modern methods such as non-probabilistic sampling via web-based enrollment. In this case identification of descriptive instrumental variables is important (Keiding & Louis, 2016), which has been introduced into the tested model via moderation analysis.

There are limitations associated with the choice of the quantitative rather than qualitative research design. Some of the drawbacks of the quantitative research are inability to establish context, deeper meaning and explanation behind the responses. Employee appraisal process is a complex phenomenon, specifically so when applied to a new concept such as AI. There is a disconnect between the researcher and the respondent which is not conducive to judging the perceptions of the respondents (Rahman, 2017).

The study adopted a cross-sectional rather than longitudinal approach, which provides a snapshot of the appraisal. A longitudinal approach can assist in understanding how the employee appraisal changes with the company’s progression through the different stages of AI implementation, and the employee career growth. In addition, one of the main assumptions of the multivariate regression models is that the relationship between the predictor and dependent variables is linear which can be not the case, specifically with complex social and cognitive phenomenon.

4.9 Ethical considerations

The main ethical consideration of the research is the respondents concerns about true anonymity of their answers. While most of the items did not appear to probe any sensitive areas, the continuity commitment to organisation did. There is a possibility that there might have been bias introduced into the answers by this dimension questions.

4.10 Conclusion

The chapter gave a high-level overview of the methodology employed in the research. The next section will present the results of the quantitate findings.

5 RESULTS

5.1 Introduction

The chapter presents the results of the data analysis and includes the measurement and the structural models assessments. The measurement model establishes the reliability and validity of constructs, while the structural model gives insights whether the hypothesised relationships between variables hold.

5.2 Descriptive statistics

The data collection process took place between the 18th of July and the 19th of September 2022. 223 responses have been collected. The data was checked for quality of answers and 216 responses have been preserved. The checks included missing values and checks of presence of records with low standard deviation across the variables to identify entries where respondents treated the survey as a tick-box exercise. Subsequently, the responses in free-text entry fields were analysed, cleaned and grouped into representative categories.

The data sample statistics are shown in Table 3. 57% of respondents were males, the prevailing age was between 30 and 50 years old. 94% of the sample were residents of South Africa. 62% of them have postgraduate degree or qualification. Technical skills used at work were characteristic to 74%. Skilled workers, middle managers and senior managers each represented a third of the sample. This outcome was a direct effect of the snowballing seeding which was based on the categories of skilled worker and managers of different ranking. 93% were users of technology. For 43% of the respondents, their company was in the initial stages of AI implementation, and 33% were not sure, which indicated that within their discipline AI had not been implemented. For 17%, the company had advanced into an operational stage of AI implementation and 7% reported that their firm did not have an intent to adopt AI.

Table 3. Sample characteristics

Characteristic	*Group*	*Count*	*Percent of sample*
Gender	Male	123	57%
	Female	92	43%
	Other	1	0.5%
Age	20-29	12	6%
	30-39	76	36%
	40-49	78	37%
	>50	45	21%
Country of residence	South Africa	204	94%
	Other	12	6%
Level of education	Postgraduate degree or qualification	134	62%
	Undergraduate degree	55	25%
	Undergraduate qualification	23	11%
	High school	4	2%
Skills technicality	Technical	160	74%
	Non-technical	56	26%
Industry	Mining and energy	134	62%
	Manufacturing and production	22	10%
	Financial services and banking	16	7%
	Technology and telecommunications	13	6%
	Other	31	14%
Discipline	Management, strategy, HR and financial	95	44%
	Computer, engineering and science	72	33%
	Services	15	7%
	Technical	10	5%
	Other	24	11%
Job stratum	Middle manager	67	31%
	Senior manager	63	29%
	Skilled worker/supervisor	61	28%
	Top manager	20	9%
	Semi-skilled worker	5	2%
Comfort with technology	I am a user of technology	200	93%
	I create technology	13	6%
	I avoid using technology	2	1%
Stage of AI implementation	Initial stages of AI implementation	92	43%
	I am not sure	72	33%
	AI is implemented and operational	36	17%
	No intent of implementing	16	7%

An analysis of the proportions in the collected demographics allowed to understand which of them could be used as moderators in the model. Descriptive variables where major categories were in excess of 30% of a sample were considered. This was done to ensure samples of sufficient size to facilitate meaningful moderation analysis. A sufficient sample size is recommended to detect a moderating effect, ideally by conducting a power analysis (Memon, Cheah, Ramayah, Chuah & Cham, 2019; Aguinis, Edwards & Bradley, 2017). The authors suggested to balance the sample size across different categories of the moderator, by having similar proportions.

Among the preserved 216 responses, a few items had null values. It was deemed acceptable to keep such responses and impute the missing values. The standard deviation of each measured variable approximated 1.0, albeit the untransformed mean deviated from 2.5 which would be ideal for a Gaussian-shaped distribution. The descriptive statistics of the variables are shown in Table 4. The histograms of the items can be found in Appendix 2. Due to PLS efficiency in dealing with non-normal data, the distributions of the variables were deemed appropriate for further processing in their raw form.

Table 4. Descriptive statistics of the sample

			Before imputing missing values						After imputing missing values			
Higher order construct	***Single-order or lower order construct***	***Item***	***N***	***Minimum***	***Maximum***	***Mean***	***Std. Dev.***	***Number of impuited samples***	***Std.Dev. after imputing***	***Variance***	***Skewness***	***Kurtosis***
	Employee subjective knowledge of AI	EK1	215	1	5	3.153	1.046	1	1.043	1.088	0.010	-0.617
		EK2	216	1	5	3.338	1.186	0	1.186	1.406	-0.208	-0.892
		EK3	215	1	5	2.442	1.142	1	1.139	1.298	0.402	-0.583
		EK4	216	1	5	3.380	1.093	0	1.093	1.195	-0.390	-0.315
		EK5	216	1	5	3.250	1.186	0	1.186	1.407	-0.260	-0.708
Perceived cognitive capabilities of AI	Context understanding	CCcxt1	216	1	5	3.481	1.021	0	1.021	1.042	-0.413	-0.295
		CCcxt2	215	1	5	3.558	1.079	1	1.076	1.158	-0.514	-0.468
		CCcxt3	216	1	5	3.926	0.902	0	0.902	0.813	-0.814	0.608
	Logic transparency	CClog1	215	1	5	3.819	0.917	1	0.915	0.837	-0.808	0.779
		CClog2	215	1	5	3.753	0.902	1	0.899	0.809	-0.730	0.723
		CClog3	216	2	5	4.134	0.804	0	0.804	0.647	-0.682	-0.021
	Language understanding	CClng1	213	1	5	3.545	1.113	3	1.106	1.222	-0.520	-0.476
		CClng2	216	1	5	3.676	0.953	0	0.953	0.908	-0.546	-0.064
		CClng3	216	1	5	3.380	1.106	0	1.106	1.223	-0.338	-0.682
Perceived operational capabilities of AI	Reliability	OCrel1	216	1	5	3.819	0.813	0	0.813	0.660	-0.445	0.120
		OCrel2	216	1	5	3.866	0.804	0	0.804	0.647	-0.455	0.440
		OCrel3	216	1	5	3.750	0.891	0	0.891	0.793	-0.444	-0.270
	Flexibility	OCflx1	216	1	5	4.046	0.776	0	0.776	0.602	-0.683	0.712
		OCflx2	215	1	5	3.716	0.921	1	0.919	0.845	-0.710	0.337
		OCflx3	215	1	5	3.633	0.967	1	0.964	0.930	-0.711	0.315
	Integrability	OCint1	216	1	5	4.194	0.747	0	0.747	0.557	-1.010	2.163
		OCint2	216	2	5	4.176	0.776	0	0.776	0.601	-0.799	0.444
		OCint3	216	2	5	4.157	0.761	0	0.761	0.580	-0.720	0.344
Anticipated adverse outcomes	Job-related	AOjob1	216	1	5	2.366	1.276	0	1.276	1.628	0.588	-0.789
		AOjob2	216	1	5	2.699	1.196	0	1.196	1.430	0.204	-0.891
		AOjob3	216	1	5	2.093	1.035	0	1.035	1.070	0.958	0.583
	Humanity-related	AOhum1	215	1	5	2.921	1.249	1	1.246	1.552	0.166	-1.048
		AOhum2	215	1	5	3.107	1.330	1	1.327	1.761	-0.114	-1.143
		AOhum3	215	1	5	2.651	1.341	1	1.338	1.790	0.413	-1.034
	Employee affective attitude towards AI	EAaff1	216	1	5	3.833	0.879	0	0.879	0.772	-0.457	0.168
		EAaff2	216	1	5	3.954	0.856	0	0.856	0.733	-0.495	-0.158
		EAaff3	216	2	5	3.875	0.829	0	0.829	0.687	-0.307	-0.501
	Employee cognitive attitude towards AI	EAcog1	216	2	5	3.963	0.765	0	0.765	0.585	-0.126	-0.815
		EAcog2	216	1	5	3.977	0.870	0	0.870	0.758	-0.681	0.138
		EAcog3	216	2	5	4.111	0.739	0	0.739	0.546	-0.319	-0.674
	Intention to use company AI	BRuse1	216	1	5	4.042	0.911	0	0.911	0.831	-0.827	0.335
		BRuse2	216	1	5	4.153	0.807	0	0.807	0.651	-0.875	0.808
		BRuse3	216	1	5	3.963	0.934	0	0.934	0.873	-0.547	-0.455
	Intention to leave the company	BRlea1	216	1	5	1.593	0.790	0	0.790	0.624	1.206	1.045
		BRlea2	216	1	5	1.866	0.844	0	0.844	0.712	0.587	-0.319
		BRlea3	214	1	4	1.888	0.826	2	0.822	0.676	0.466	-0.720
		BRlea4	215	1	5	2.005	0.894	1	0.892	0.795	0.428	-0.579
	Perceived organisational support	POS1	216	1	5	3.398	1.082	0	1.082	1.171	-0.424	-0.380
		POS2	216	1	5	3.519	1.078	0	1.078	1.162	-0.520	-0.206
		POS3	216	1	5	3.583	1.109	0	1.109	1.230	-0.460	-0.536
		POS4	216	2	5	4.097	0.750	0	0.750	0.563	-0.495	-0.120
		POS5	216	1	5	3.306	0.988	0	0.988	0.976	-0.236	-0.261
		POS6	216	1	5	3.236	0.995	0	0.995	0.991	-0.089	-0.338
		POS7	216	1	5	3.208	1.145	0	1.145	1.310	0.135	-0.765
		POS8	216	1	5	2.352	1.085	0	1.085	1.178	-0.563	-0.296
Commitment to organisation	Affective	COaff1	216	1	5	3.361	1.212	0	1.212	1.469	-0.391	-0.685
		COaff2	216	1	5	3.421	1.105	0	1.105	1.222	-0.456	-0.404
		COaff3	215	1	5	3.665	1.119	1	1.116	1.246	-0.563	-0.437
		COaff4	215	1	5	3.405	1.207	1	1.204	1.450	-0.338	-0.863
		COaff5	216	1	5	3.560	1.152	0	1.152	1.327	-0.480	-0.561
		COaff6	215	1	5	3.423	1.133	1	1.130	1.277	-0.305	-0.713
	Continuance	COcnt1	214	1	5	2.888	1.299	2	1.293	1.671	0.081	-1.084
		COcnt2	215	1	5	2.777	1.255	1	1.253	1.569	0.158	-0.932
		COcnt3	215	1	5	2.726	1.269	1	1.266	1.604	0.253	-0.967
		COcnt4	215	1	5	2.647	1.146	1	1.144	1.308	0.237	-0.735
		COcnt5	215	1	5	2.405	1.093	1	1.091	1.190	0.529	-0.322
		COcnt6	216	1	5	2.852	1.230	0	1.230	1.513	0.089	-0.969
	Normative	COnrm1	216	1	5	2.875	1.212	0	1.212	1.468	0.116	-0.913
		COnrm2	216	1	5	2.542	1.149	0	1.149	1.319	0.408	-0.636
		COnrm3	216	1	5	2.329	1.216	0	1.216	1.477	0.664	-0.487
		COnrm4	216	1	5	3.000	1.205	0	1.205	1.451	-0.145	-0.780
		COnrm5	213	1	5	2.840	1.191	3	1.182	1.398	-0.009	-0.855
		COnrm6	213	1	5	2.911	1.176	3	1.168	1.364	-0.072	-0.862

5.3 Measurement model testing

Due to presence of HOCs in the model, the measurement model was tested with disjoint two-stage approach. In stage one of the approach, the exogenous LOCs were tested for the direct relationships with relevant endogenous constructs, while HOCs were excluded. In the same run, all other single-order constructs were validated as well. In the second stage, the latent variable scores created in the stage one, were treated as measurement indicators. It allowed to test the model inclusive of HOCs.

5.3.1 <u>Stage 1. Assessing LOCs</u>

To assess for the LOCs, factor loadings were tested first, followed by reliability and validity tests. The LOCs were connected directly in the model, without the HOCs, to enable this. The model is shown in Figure 4.

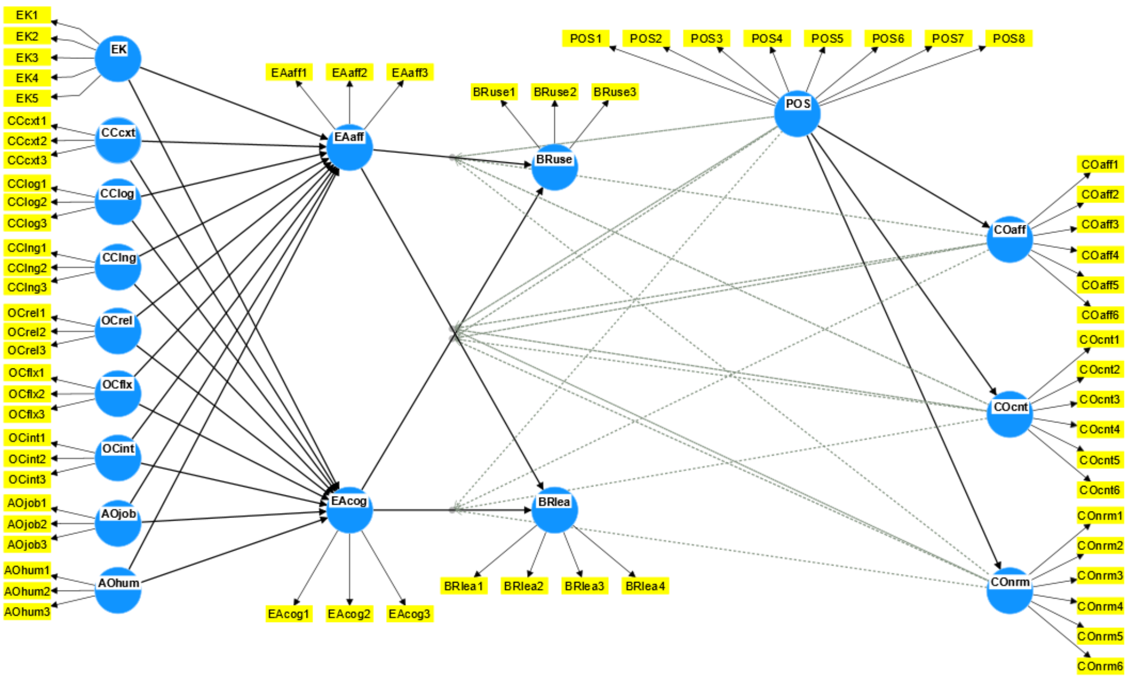

Figure 4. Diagram of the research model used in the first stage of the two-stage disjoint approach of the measurement model testing

A few runs of LOC measurement model testing were conducted, to remove poorly performing items. The details of the exercise can be found in Section 5.3.1.5. Sections 5.3.1.1 - 5.3.1.4 present the assessment results for the preserved measurement model items. Conducting different types of measurement analysis on this set showed that all the LOCs had a good performance. The summary is presented in Table 5 with details described in sections below.

5.3.1.1 Factor loadings

The absolute threshold value less than 0.5 (Hair et al., 2017) was used to flag items of concern in this study. The factor loadings are shown in Table 5. In the final run of assessment, they are all acceptable, exceeding 0.5.

Table 5. Lower-order and single-order constructs measurement model validation

Item	Factor loadings	Cronbach's alpha	CR	AVE	VIF
AOhum1	0.884	0.854	0.911	0.774	2.273
AOhum2	0.848				1.870
AOhum3	0.906				2.399
AOjob1	0.851	0.779	0.869	0.689	2.101
AOjob2	0.806				1.834
AOjob3	0.832				1.408
BRlea1	0.761	0.804	0.872	0.632	1.543
BRlea2	0.803				1.750
BRlea3	0.876				2.257
BRlea4	0.732				1.582
BRuse1	0.945	0.931	0.956	0.879	4.222
BRuse2	0.918				3.207
BRuse3	0.950				4.641
CCcxt1	0.709	0.704	0.832	0.625	1.287
CCcxt2	0.870				1.467
CCcxt3	0.784				1.420
CClng1	0.876	0.830	0.898	0.745	1.999
CClng2	0.865				1.775
CClng3	0.848				1.978
CClog1	0.768	0.731	0.842	0.639	1.609
CClog2	0.790				1.631
CClog3	0.839				1.283
COaff1	0.747	0.852	0.890	0.574	1.690
COaff2	0.702				1.572
COaff3	0.731				2.194
COaff4	0.808				2.301
COaff5	0.790				2.238
COaff6	0.764				1.782
COcnt1	0.917	0.653	0.758	0.523	1.150
COcnt2					
COcnt3					
COcnt4	0.678				1.492
COcnt5					
COcnt6	0.519				1.424
COnrm1	0.633	0.846	0.886	0.566	1.390
COnrm2	0.680				1.757
COnrm3	0.785				2.263
COnrm4	0.796				1.728
COnrm5	0.785				2.054
COnrm6	0.816				2.121
EAaff1	0.962	0.918	0.961	0.925	3.587
EAaff2	0.961				3.587
EAaff3					
EAcog1	0.930	0.916	0.947	0.857	3.336
EAcog2	0.924				3.183
EAcog3	0.923				3.198
EK1	0.790	0.826	0.877	0.590	1.799
EK2	0.712				1.621
EK3	0.729				1.560
EK4	0.800				1.875
EK5	0.803				2.084
OCflx1	0.873	0.829	0.892	0.735	1.583
OCflx2	0.889				2.832
OCflx3	0.807				2.358
OCint1	0.910	0.914	0.946	0.854	2.794
OCint2	0.949				4.221
OCint3	0.913				3.296
OCrel1	0.838	0.805	0.885	0.720	1.720
OCrel2	0.894				2.165
OCrel3	0.813				1.659
POS1	0.801	0.855	0.892	0.585	2.094
POS2	0.897				4.131
POS3	0.891				3.773
POS4	0.658				1.430
POS5	0.631				1.578
POS6	0.661				1.651
POS7					
POS8					

5.3.1.2 Collinearity

The degree of multicollinearity was established by analysing the VIF. A threshold of 5.0 has been used (Hair et al., 2021). The final results of the multicollinearity testing of the LOCs are shown in the last column in Table 5, they are all acceptable.

5.3.1.3 Reliability

The approaches used for testing the reliability in the research were Cronbach's alpha and CR. The accepted threshold for both was 0.6 (Hair et al., 2019b). After the deletion of the items as described in Section 5.3.1.5 below, the final Cronbach's alpha and CR values for all single-order and LOCs were acceptable (Table 5), confirming good reliability of the measurement model.

5.3.1.4 Validity

The construct validity is ensured when two components produce satisfactory results, namely convergent validity and discriminant validity.

Convergent validity

When the AVE value is >0.5, the different items are said to "converge" in measuring the underlying construct (Hair et al., 2021). All the LOCs and single-order constructs in the model (Table 5) showed acceptable levels of AVE.

Discriminant validity

A number of parameters were used to test the discriminant validity: the Fornell-Larcker criterion, HTMT ratio and cross-loadings. Fornell-Larcker criterion represents a square root of AVE and is deemed acceptable when its value is greater than the shared variance of the construct with any other construct in the model. Table 6 demonstrates that for all LOCs in the model, the condition is satisfied.

Table 6. Discriminant validity: Fornell-Larcker criterion

Constructs	AOhum	AOjob	BRlea	BRuse	CCcxt	CClng	CClog	COaff	COcnt	COnrm	EAaff	EAcog	EK	OCflx	OCint	OCrel	POS
AOhum	0.880																
AOjob	0.582	0.830															
BRlea	0.328	0.332	0.795														
BRuse	-0.410	-0.362	-0.498	0.938													
CCcxt	-0.071	-0.030	-0.199	0.318	0.790												
CClng	-0.123	-0.022	-0.302	0.326	0.630	0.863											
CClog	-0.118	-0.083	-0.258	0.351	0.631	0.553	0.800										
COaff	-0.097	-0.118	-0.279	0.040	-0.079	0.062	0.105	0.758									
COcnt	0.076	0.244	0.105	-0.005	0.203	0.229	0.111	-0.389	0.672								
COnrm	0.095	0.070	-0.143	-0.157	-0.097	0.039	-0.008	0.652	-0.205	0.752							
EAaff	-0.548	-0.442	-0.528	0.680	0.330	0.410	0.368	0.186	-0.016	-0.021	0.962						
EAcog	-0.555	-0.447	-0.558	0.722	0.269	0.356	0.318	0.167	-0.082	-0.100	0.786	0.926					
EK	-0.325	-0.259	-0.318	0.460	0.170	0.222	0.220	0.047	-0.117	-0.108	0.465	0.375	0.768				
OCflx	-0.131	-0.051	-0.293	0.282	0.503	0.650	0.570	0.112	0.109	0.092	0.376	0.314	0.298	0.857			
OCint	-0.029	-0.134	-0.210	0.396	0.399	0.491	0.413	-0.030	-0.064	-0.119	0.350	0.342	0.266	0.489	0.924		
OCrel	-0.084	-0.089	-0.321	0.355	0.493	0.553	0.526	0.081	0.000	-0.018	0.388	0.384	0.181	0.591	0.525	0.849	
POS	-0.045	-0.155	-0.222	0.085	0.019	0.039	0.129	0.672	-0.380	0.479	0.157	0.151	-0.020	0.105	0.096	0.206	0.765

The HTMT ratio was assessed against the threshold of 0.85 (Hair et., 2021; Henseler et al., 2015; Hair et al., 2022). Only one value was above it, namely CClog-CCcxt. This is because both variables belong to the same HOC and might be hard to distinguish. When similar constructs exist, a threshold of 0.90 is deemed acceptable. For the purpose of the study, it was accepted as it.

Table 7. Discriminant validity: Heterotrait-monotrait ratio matrix

	AOhum	AOjob	BRlea	BRuse	CCcxt	CClng	CClog	COaff	COcnt	COnrm	EAaff	EAcog	EK	OCflx	OCint	OCrel	POS
AOhum																	
AOjob	0.713																
BRlea	0.39	0.4															
BRuse	0.458	0.403	0.571														
CCcxt	0.091	0.145	0.272	0.387													
CClng	0.145	0.15	0.363	0.361	0.809												
CClog	0.137	0.13	0.333	0.4	0.915	0.712											
COaff	0.118	0.141	0.337	0.082	0.149	0.127	0.149										
COcnt	0.122	0.346	0.185	0.061	0.239	0.292	0.16	0.378									
COnrm	0.155	0.09	0.202	0.176	0.155	0.115	0.139	0.745	0.304								
EAaff	0.616	0.5	0.612	0.734	0.395	0.463	0.428	0.211	0.072	0.074							
EAcog	0.626	0.518	0.648	0.78	0.329	0.405	0.364	0.186	0.115	0.126	0.856						
EK	0.377	0.289	0.394	0.515	0.219	0.268	0.267	0.108	0.152	0.142	0.528	0.423					
OCflx	0.148	0.108	0.35	0.307	0.658	0.797	0.726	0.165	0.201	0.122	0.405	0.336	0.359				
OCint	0.052	0.149	0.239	0.43	0.497	0.554	0.482	0.059	0.162	0.134	0.38	0.373	0.303	0.547			
OCrel	0.112	0.12	0.399	0.412	0.659	0.677	0.687	0.099	0.147	0.077	0.451	0.447	0.226	0.698	0.612		
POS	0.083	0.218	0.278	0.123	0.113	0.097	0.157	0.759	0.392	0.514	0.188	0.188	0.069	0.133	0.119	0.262	

The crossloadings exhibited a problem with continuity commitment to organisation, being less than 0.1 (Farrell, 2010). The results are shown in Table 8. This dimension of commitment has brought up different issues through the assessment of the measurement, and items COcnt2, COcnt3 and COcnt5 were deleted from the final model (see Section 5.3.1.5 below), leaving three items in the CO construct. In this step, the item was kept, but watched closely in further tests, to facilitate the decision on removal.

Table 8. Results of crossloadings assessment

Item	AO	BRlea	BRuse	CC	CO	EAaff	EAcog	EK	OC	POS
AOhum	0.964	0.329	-0.410	-0.135	-0.100	-0.548	-0.555	-0.325	-0.094	-0.048
AOjob	0.777	0.333	-0.362	-0.052	-0.147	-0.442	-0.447	-0.259	-0.112	-0.156
BRlea1	0.346	0.765	-0.433	-0.203	-0.165	-0.430	-0.481	-0.225	-0.177	-0.167
BRlea2	0.297	0.806	-0.419	-0.240	-0.193	-0.417	-0.445	-0.215	-0.290	-0.167
BRlea3	0.328	0.874	-0.439	-0.346	-0.214	-0.485	-0.475	-0.311	-0.364	-0.168
BRlea4	0.168	0.727	-0.282	-0.217	-0.297	-0.337	-0.365	-0.256	-0.218	-0.225
BRuse1	-0.461	-0.486	0.945	0.350	0.014	0.667	0.712	0.436	0.353	0.065
BRuse2	-0.357	-0.411	0.918	0.331	0.014	0.588	0.633	0.391	0.377	0.077
BRuse3	-0.402	-0.502	0.950	0.389	0.070	0.655	0.682	0.463	0.447	0.114
CCcxt	-0.065	-0.199	0.318	0.726	-0.111	0.330	0.269	0.170	0.558	0.022
CClng	-0.102	-0.302	0.326	0.925	0.017	0.409	0.356	0.222	0.668	0.041
CClog	-0.118	-0.257	0.351	0.828	0.075	0.368	0.318	0.220	0.601	0.133
COaff	-0.113	-0.278	0.040	0.085	0.988	0.186	0.167	0.047	0.064	0.672
COcnt	0.146	0.084	-0.011	0.216	-0.530	-0.003	-0.057	-0.130	0.025	-0.387
COnrm	0.097	-0.141	-0.157	0.019	0.653	-0.021	-0.100	-0.108	-0.026	0.470
EAaff1	-0.552	-0.518	0.633	0.442	0.185	0.962	0.749	0.464	0.450	0.180
EAaff2	-0.541	-0.498	0.676	0.411	0.140	0.961	0.762	0.429	0.407	0.128
EAcog1	-0.576	-0.562	0.648	0.328	0.163	0.753	0.930	0.372	0.359	0.158
EAcog2	-0.500	-0.520	0.673	0.411	0.164	0.711	0.925	0.364	0.421	0.171
EAcog3	-0.521	-0.467	0.683	0.328	0.113	0.718	0.923	0.304	0.393	0.108
EK1	-0.210	-0.202	0.358	0.268	-0.003	0.360	0.314	0.790	0.292	-0.033
EK2	-0.217	-0.237	0.257	0.174	0.005	0.337	0.249	0.712	0.279	-0.077
EK3	-0.243	-0.270	0.409	0.228	0.118	0.380	0.285	0.729	0.177	0.035
EK4	-0.388	-0.223	0.404	0.137	0.090	0.389	0.342	0.800	0.159	0.000
EK5	-0.204	-0.300	0.310	0.141	0.011	0.299	0.225	0.803	0.194	-0.007
OCflx	-0.118	-0.291	0.282	0.698	0.088	0.376	0.314	0.298	0.796	0.107
OCint	-0.066	-0.211	0.396	0.520	-0.025	0.350	0.342	0.266	0.797	0.099
OCrel	-0.094	-0.321	0.355	0.614	0.071	0.388	0.384	0.181	0.889	0.212
POS1	-0.037	-0.192	0.019	0.069	0.578	0.106	0.082	-0.002	0.133	0.792
POS2	-0.050	-0.156	-0.002	0.047	0.611	0.095	0.084	-0.043	0.115	0.888
POS3	-0.023	-0.158	0.032	0.068	0.649	0.097	0.071	-0.012	0.096	0.885
POS4	-0.081	-0.283	0.168	0.170	0.491	0.195	0.257	-0.011	0.226	0.683
POS5	-0.157	-0.132	0.143	0.024	0.358	0.178	0.153	-0.010	0.157	0.632
POS6	-0.113	-0.097	0.116	-0.010	0.365	0.089	0.108	-0.008	0.105	0.664

5.3.1.5 Item refinement and elimination

Two constructs, POS and CO, have exhibited some problems and a few items within them had to be eliminated. The relevant details are provided below.

A number of iterations of confirmatory factor analysis were undertaken to assess the measurement model performance and remove a few poorly performing items. Four items displayed low factor loadings values, namely, COcnt2, COcnt2, POS7 and PO8. The reason for poor results from POS7 ("If given the opportunity, my organisation would take full advantage of me") and POS8 ("My organisation shows very little consideration for me") are attributed to the fact that respondents might have felt the organisation did not treat them as bad as these questions implied. Namely, the gravity of phrasing these questions was extreme in comparison to the remaining six questions of the continuance commitment construct and might necessitate an extra dimension within the POS construct in future studies. Having a low factor loading on its own was not a sufficient reason for removing the item (Hair et al., 2019b). These two items were eliminated after conducting PCA and analysing an eigenvalue component matrix.

In addition to poor factor loadings for COcnt2 and COcnt3, the item COcnt5 showed to be slightly below the threshold of 0.3 in the PCA matrix, displaying a value of 0.275. The eigen component matrix lacked distinct grouping for this indicator on either Component 1 or 2. The reason behind poor performance of COcnt2, COcnt3 and

COcnt5 grants further investigation, which is beyond the scope of the current study. It was decided to delete all three items.

In the early runs of the validation, the check for reliability showed that the POS construct had Cronbach's alpha below the required threshold of 0.6 (Hair et al., 2019b) and AVE values below 0.5 (Hair et al., 2019b). The COcnt construct had a low AVE value. These findings further confirmed a need to delete POS7 and POS8 as well as COcnt2, COcnt3 and COcnt5.

The first round of multicollinearity testing showed acceptable VIF values for all the items in the model, except EAaff, where two out of the three had VIF values in access of 5.0. In the final run, one item was deleted, namely, EAaff3, which stabilised the results of the remaining two items in the construct. In summary, the items COcnt2, COcnt3, COcnt5, EAaff3, POS7 and POS8 were deleted from the model.

5.3.2 Stage 2. Assessing HOCs

In the second step of the disjoint two-step approach, the model was adjusted to include the newly formed LOCs of the constructs CC, OC, AO and CO as items. Formative links were ensured from them to the HOCs. The structural model used at this stage is shown in Figure 5. The testing of the HOCs comprised of collinearity and significance and relevance of outer weights (Sarstedt et al., 2019).

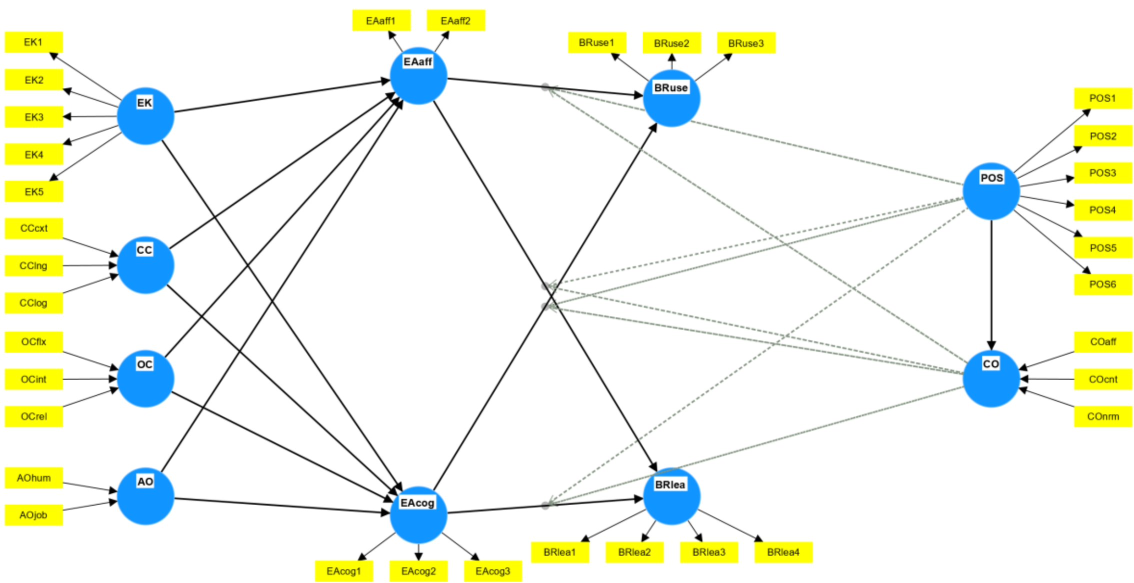

Figure 5. Diagram of the research model reflecting the second step in the two-stage disjoint approach of the measurement model testing

5.3.2.1 Collinearity

The formative measurement model for the HOCs, similarly to LOCs, did not exhibit any collinearity issues, with all the VIF coefficients below 5.0, as shown in the last column of Table 9.

Table 9. Results of higher-order constructs assessment for outer weights, outer loadings and VIF

HOC	LOC	Outer weight			Outer loadings		VIF
		Value	T statistics	P values	Value	P values	
AO	AOhum	0.774	8.788	0.000	0.964	0.000	1.511
	AOjob	0.327	3.079	0.002	0.777	0.000	1.511
CC	CCcxt	0.030	0.148	0.883	0.726	0.000	2.047
	CClng	0.660	3.771	0.000	0.925	0.000	1.775
	CClog	0.445	2.557	0.011	0.828	0.000	1.780
CO	COaff	0.908	8.439	0.000	0.988	0.000	1.948
	COcnt	-0.167	2.032	0.042	-0.530	0.000	1.185
	COnrm	0.022	0.160	0.873	0.653	0.000	1.741
OC	OCflx	0.311	1.787	0.074	0.796	0.000	1.647
	OCint	0.378	2.440	0.015	0.797	0.000	1.480
	OCrel	0.507	3.020	0.003	0.889	0.000	1.730

5.3.2.2 Significance and relevance of outer weights and outer loadings

To assess the outer weights and outer loadings, bootstrapping was performed with 5,000 subsamples. At a significance value of 0.05, the outer weights were found significant for all items except CCcxt (p-value=0.883), COnrm (p-value=0.873) and OCflx (p-value=0.074). They are shown in blue in Table 9. Hair et al. (2017) recommended for formative measurement models, as in case of the current study, outer weights to be the main criterion of assessment as they are a result of multiple regression of the construct on the indicators. The authors also suggested that non-significance of the indicator weight might not point towards poor quality of the measurement model. In this case, the absolute contribution in the form of the indicator loading should be analysed, with a minimum requirement being the significance of the loading. If the indicator loading is equal to or higher than 0.5 then its contribution to the formative construct is sufficiently high, even when the relative contribution is insignificant.

The analysis of the outer loadings (Table 9) showed that the three items of concern all had acceptable values of outer loadings, in excess of 0.5, and significant p-values lower than 0.05. These items, namely CCcxt, COnrm and OCflx, were preserved. However, the COcnt variable showed a low outer loading, below 0.5. Combined with the negative outer weight it indicated that this dimension measured the opposite of the CO construct. Hair et al. (2017) recommended in such a case to consider the variable for removal. In the course of this study, the performance of the COcnt had shown problems before. Going forward, this dimension was removed from the commitment to organisation HOC.

The relevance of each indicator to the corresponding formative construct is expressed by the absolute value of the indicator weight. As such, the AOhum has a higher contribution to AO, CClng to CC, COaff to CO, and OCrel to OC (Table 9).

5.4 Structural model testing

Smart-PLS 4.0 was used for testing the structural model. Sarstedt et al. (2019) suggested testing the structural model using the output of the second stage of the disjoint two-stage approach. The approach adopted for the structural model testing comprised of four steps assessing: 1) test for presence of collinearity, 2) significance and relevance in the paths of the structural model, 3) explanatory power, and 4) predictive power of the model.

5.4.1 Collinearity

Assessing collinearity in the structural model revealed that while all the direct relationships did not exhibit any collinearity (were below 5.0), the moderating effects from POS to interactions of EAaff -> BRlea, EAaff -> BRuse, EAcog -> BRlea, EAcog -> BRuse had collinearity issues (Table 10). A number of approaches exist for moderation analysis, among which a two-stage method has been recommended when the independent or the moderator variables are formative (Memon et al., 2019; Fassot et al., 2016). This is the case in the current model, with the POS construct being measured formatively. While this approach can also produce collinearity (Memon et al., 2019), it should be attempted in future. At this step, the collinearity issues were accepted.

Table 10. Structural model collinearity statistics

	BRlea	*BRuse*	*CO*	*EAaff*	*EAcog*
AO				1.130	1.130
CC				2.120	2.120
CO	1.907	1.907			
EAaff	2.853	2.853			
EAcog	2.727	2.727			
EK				1.216	1.216
OC				2.161	2.161
POS	1.952	1.952	1.000		
CO x EAcog	4.897	4.897			
POS x EAaff	5.580	5.580			
CO x EAaff	3.904	3.904			
POS x EAcog	6.354	6.354			

5.4.2 Structural model significance and relevance assessment

5.4.2.1 Model direct relationships

The results of the significance and relevance testing are present in Table 11, with a short description below. One-tail bootstrapping test in PLS was conducted based on 5,000 subsamples. Out of 12 direct path tests, only one (H2a) did not show a significant level of relationship.

In addition to hypothesised relationships, another direct relationship in the model was also assessed, namely between POS and CO. It showed a positive significant relationship between perceived organisational support and commitment to organisation.

Table 11. Summary of statistical testing for direct relationships

Hypothesis ID	*Path effect tested*	*B*	*Std.Dev.*	*T-statistic*	*P-value*	*Results*
		Hypothesised relationships				
H1a	EK -> EAaff	0.208	0.055	3.811	0.000	Supported
H1b	EK -> EAcog	0.106	0.055	1.934	0.027	Supported
H2a	CC -> EAaff	0.194	0.066	2.924	0.002	Supported
H2b	CC -> EAcog	0.111	0.073	1.528	0.063	Not supported
H3a	OC -> EAaff	0.196	0.065	3.037	0.001	Supported
H3b	OC -> EAcog	0.257	0.080	3.205	0.001	Supported
H4a	AO -> EAaff	-0.453	0.053	8.555	0.000	Supported
H4b	AO -> EAcog	-0.498	0.054	9.205	0.000	Supported
H5a	EAaff -> BRuse	0.308	0.079	3.876	0.000	Supported
H5b	EAaff -> BRlea	-0.206	0.096	2.135	0.016	Supported
H6a	EAcog -> BRuse	0.495	0.076	6.476	0.000	Supported
H6b	EAcog -> BRlea	-0.364	0.088	4.124	0.000	Supported
		Not hypothesised relationships				
	POS -> CO	0.673	0.037	18.333	0.000	Supported

The description of hypotheses testing outcomes is spelled out below.

H1a. Employee knowledge of AI is positively associated with affective attitude toward AI (EK – EAaff).

Employee knowledge of AI has a significant and positive association with affective attitude toward AI (β =0.208, t=3.811, p=0.000). H1b is supported.

H1b. Employee knowledge of AI is positively associated with cognitive attitude toward AI (EK - EAcog).

Employee knowledge of AI has a significant and positive association with the cognitive attitude toward AI (β =0.106, t=1.934, p=0.027). H1a is supported.

H2a. Cognitive capabilities of AI as perceived by an employee have a positive association with his/her affective attitude toward AI (CC – EAaff).

Perceived cognitive capabilities of AI have a positive but not significant association with cognitive attitude toward AI (β =0.111, t=1.528, p=0.063). H2a is not supported.

H2b. Cognitive capabilities of AI as perceived by an employee have a positive association with his/her cognitive attitude toward AI (CC – EAcog).

Perceived cognitive capabilities of AI have a significant and positive association with the affective attitude toward AI (β =0.194, t=2.924, p=0.002). H2b is supported.

H3a. Operational capabilities of AI as perceived by an employee have a positive association with his/her affective attitude toward AI (OC – EAaff).

Perceived operational capabilities of AI have a significant and positive association with the cognitive attitude toward AI (β =0.257, t=3.205, p=0.001). H3a is supported.

H3b. Operational capabilities of AI as perceived by an employee have a positive association with his/her cognitive attitude toward AI (OC – EAcog).

Perceived operational capabilities of AI have a significant and positive association with the affective attitude toward AI (β =0.196, t=3.037, p=0.001). H3b is supported.

H4a. Anticipated adverse outcomes of AI as perceived by an employee have a negative association with affective attitude toward AI (AO – EAaff).

Anticipated adverse outcomes of AI have a significant and negative association with the employee's affective attitude toward AI (β =-0.453, t=8.555, p=0.000). H4b is supported.

H4b. Anticipated adverse outcomes of AI as perceived by an employee have a negative association with cognitive attitude toward AI (AO – EAcog).

Anticipated adverse outcomes of AI have a significant and negative association with the employee's cognitive attitude toward AI (β =-0.498, t=9.205, p=0.000). H4a is supported.

H5a. Affective attitude toward AI is positively associated with intention to use enterprise AI (EAaff – BRuse).

Employee affective attitude toward AI has a significant and positive association with the employee's intention to use enterprise AI (β =0.308, t=3.876, p=0.000). H6a is supported.

H5b. Affective attitude toward AI is negatively associated with intention to leave the organisation if AI is implemented (EAaff – BRlea).

Employee affective attitude toward AI has a significant and negative association with the employee's intention to leave the organisation if AI is implemented (β =-0.206, t=2.135, p=0.016). H6b is supported.

H6a. Cognitive attitude toward AI is positively associated with intention to use enterprise AI (EAcog – BRuse).

Employee cognitive attitude toward AI has a significant and positive association with the employee's intention to use enterprise AI (β =0.495, t=6.476, p=0.000). H5a is supported.

H6b. Cognitive attitude toward AI is negatively associated with intention to leave the organisation if AI is implemented (EAcog – BRlea).

Employee cognitive attitude toward AI has a significant and negative association with the employee's intention to leave the organisation if AI is implemented (β=-0.364, t=4.124, p=0.000). H5b is supported.

In addition, a non-hypothesised relationship has been found significant: perceived organisational support has a significant and positive association with the employee commitment to organisation (β=0.673, t=18.333, p=0.000).

5.4.2.2 Model indirect relationships

Indirect relationships testing comprised of moderation and mediated moderation analysis.

POS moderating effect on the employee attitudes – behavioral outcomes paths

Testing for the moderating effect of POS on the four paths between the employee attitudes and the behavioral outcomes showed that all four paths were insignificant, indicating that no significant direct moderation existed (Table 12).

Table 12. Summary of statistical testing for indirect relationships: moderation by POS

Hypothesis ID	***Path effect tested***	***B***	***Std.Dev.***	***T-statistic***	***P-value***	***Results***
H7a	POS x EAaff -> BRuse	-0.042	0.106	0.402	0.344	Not supported
H7b	POS x EAaff -> BRlea	0.057	0.150	0.378	0.353	Not supported
H7c	POS x EAcog -> BRuse	-0.025	0.109	0.232	0.408	Not supported
H7d	POS x EAcog -> BRlea	-0.024	0.137	0.172	0.432	Not supported

H7a. POS affects the relationship between affective attitude and intention to use AI such that the relationship is weakened with perceived high level of organisational support.

The perceived organisational support does not have a significant effect on the relationship between the employee affective attitude toward AI and the intention to use the organisational AI, at the significance level of p=0.05 (β =-0.042, t=0.402, p=0.344). Hypothesis H7a is not supported.

H7b. POS affects the relationship between affective attitude and intention to leave the company such that the relationship is strengthened with perceived high level of organisational support.

The perceived organisational support does not have a significant effect on the relationship between the employee affective attitude toward AI and the intention to leave the organisation if AI is implemented, at the significance level of p=0.05 (β =0.057, t=0.378, p=0.353). Hypothesis H7b is not supported.

H7c. POS affects the relationship between cognitive attitude and intention to use AI such that the relationship is weakened with perceived high level of organisational support.

The perceived organisational support does not have a significant effect on the relationship between the employee cognitive attitude toward AI and the intention to use the organisational AI, at the significance level of p=0.05 (β =-0.025, t=0.232, p=0.408). Hypothesis H7c is not supported.

H7d. POS affects the relationship between cognitive attitude and intention to leave the company such that the relationship is strengthened with perceived high level of organisational support.

The perceived organisational support does not have a significant effect on the relationship between the employee cognitive attitude toward AI and the intention to leave the organisation if AI is implemented, at the significance level of p=0.05 (β =- 0.024, t=0.172, p=0.432). Hypothesis H7d is not supported.

Mediated moderation by CO as a higher-order construct

The hypothesised mediated moderation effect of commitment to organisation on the four relationships between employee attitudes to AI and behavioral outcomes was not confirmed within the accepted 0.05 threshold of p-value. Table 13 contains the summary of the hypotheses testing results.

Table 13. Summary of statistical testing for indirect relationships: moderation by CO

Hypothesis ID	Path effect tested	B	Std.Dev.	T-statistic	P-value	Results
H8a	CO x EAaff -> BRuse	-0.070	0.090	0.784	0.216	Not supported
H8b	CO x EAaff -> BRlea	0.051	0.119	0.431	0.333	Not supported
H8c	CO x EAcog -> BRuse	0.121	0.108	1.125	0.130	Not supported
H8d	CO x EAcog -> BRlea	-0.107	0.111	0.967	0.167	Not supported

The following hypotheses have not been confirmed:

H8a. CO mediates the moderating relationship of POS on affective attitude-intention to use AI.

The employee commitment to organisation does not have a significant mediating effect on the relationship between the employee affective attitude toward AI and the intention to use the organisational AI (β =-0.070, t=0.784, p=0.216). Hypothesis H8a is not supported.

H8b. CO mediates the moderating relationship of POS on affective attitude-intention to leave the organisation.

The employee commitment to organisation does not have a significant mediating effect on the relationship between the employee affective attitude toward AI and the intention to leave the organisation if AI is implemented (β =0.051, t=0.431, p=0.333). Hypothesis H8b is not supported.

H8c. CO mediates the moderating relationship of POS on cognitive attitude-intention to use AI.

The employee commitment to organisation does not have a significant effect on the relationship between the employee cognitive attitude toward AI and the intention to use the organisational AI (β =0.121, t=1.125, p=0.130). Hypothesis H8c is not supported.

H8d. CO mediates the moderating relationship of POS on cognitive attitude - intention to leave the organisation.

The employee commitment to organisation does not have a significant effect on the relationship between the employee cognitive attitude toward AI and the intention to leave the organisation if AI is implemented (β =-0.107, t=0.967, p=0.167). Hypothesis H8d is not supported.

5.4.2.3 Post-hoc analysis

Mediated moderation by CO lower-order constructs

Through the course of the study, the CO higher-order construct showed to be a complex ambiguous construct. As a result, it was decided to test individual LOCs comprising the commitment to organisation latent variable in mediated moderation of POS on the four paths: 5a (EAaff – BRuse), 5b (EAaff – BRlea), 6a (EAcog – BRuse) and 6b (EAcog – BRlea). The three LOCs of commitment to organisation, namely, affective, continuance and normative commitment, were tested for their effect in the model separately, as single-order constructs. Assessing the model with the normative commitment single-order construct revealed significant effects of the tested path. The tested model is shown in Figure 6. The results are summarised in Table 14.

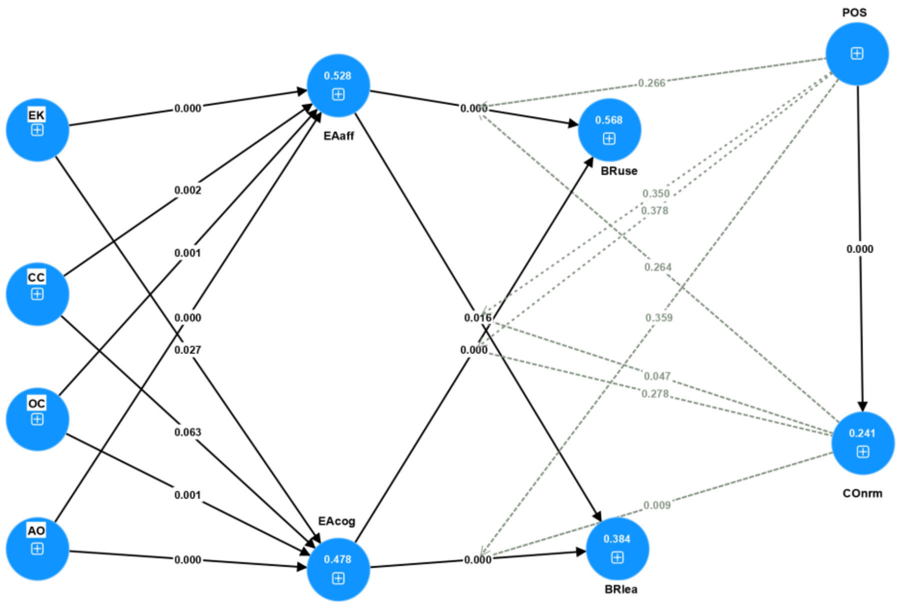

Figure 6. Model used for testing the COnrm mediation role. The p-values are displayed on the paths

In the tested mode, three effects were found to be significant: direct relationship between POS and COnrm, and two moderating relationships of COnrm: on the path between EAaff and BRlea and on EAcog - BRlea.

Table 14. Summary of statistical testing for indirect relationships: mediated moderation by COnrm

Path effect tested	***B***	***Std.Dev.***	***T-statistic***	***P-value***	***Results***
POS -> COnrm	0.491	0.048	10.156	0.000	Significant
POS x EAaff -> BRuse	-0.065	0.105	0.625	0.266	Not significant
POS x EAaff -> BRlea	0.047	0.121	0.386	0.350	Not significant
POS x EAcog -> BRuse	0.031	0.099	0.311	0.378	Not significant
POS x EAcog -> BRlea	-0.041	0.113	0.360	0.359	Not significant
COnrm x EAaff -> BRlea	0.147	0.087	1.678	0.047	Significant
COnrm x EAaff -> BRuse	-0.050	0.080	0.630	0.264	Not significant
COnrm x EAcog -> BRlea	-0.179	0.076	2.366	0.009	Significant
COnrm x EAcog -> BRuse	0.049	0.084	0.588	0.278	Not significant

Following the decision map suggested by Hair et al. (2019b) (Figure 3), the type of the mediating role of COnrm for the two significant paths, EAcog – BRlea and EAaff – BRlea, was determined. For each of these two paths, the interaction term $p_1 * p_2$ was significant, 0.009 and 0.047 respectively. On the other hand, the p_3 term which represented the moderating effect of POS on each of the path was not significant. This suggested that there was full mediation of POS on EAaff – BRlea and EAcog – BRlea, via COnrm.

Figure 7 demonstrates the moderating effect. As can be seen in Figure 7a, lower levels of normative commitment to organisation (blue line) result in a stronger effect of employee affective attitude to AI on the intent to leave the company. Figure 7b shows that at higher levels of normative commitment to organisation (red line), the cognitive attitude of employee to AI has a stronger correlation with his/her intention to leave the organisation than at lower levels of normative commitment.

a) b)

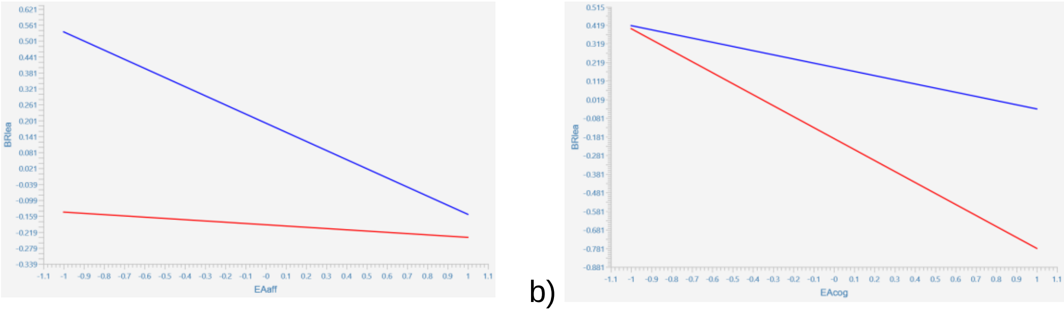

Figure 7. Slope analysis graphs for the moderating effect of COnrm on: a) EAcog and BRlea path, b) EAaff and BRuse path. Blue line signifies low level of COnrm, red line – high level

As a result of the fundings above the model has been refined as follows:

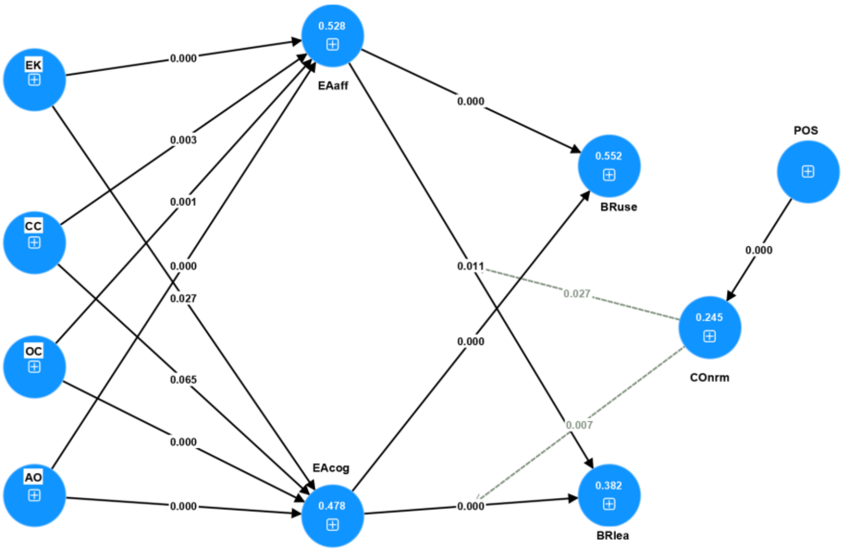

Figure 8. Final model used in the study. The p-values are displayed on the paths

Categorical variable moderation

Moderation tests were conducted to understand if any characteristics of the respondents would affect the relationships expressed by hypotheses 5a (EAaff – BRuse), 5b (EAaff – BRlea), 6a (EAcog – BRuse) and 6b (EAcog – BRea). The moderating role of following characteristics was tested: gender, technicality of the degree, job level (skilled worker/supervisor, middle management, senior management) and stage of AI implementation (AI not implemented/not aware of AI implementation status, initial stages of AI implementation, AI implemented and operational).

The technicality of the degree showed to have no moderating effect. So did the managerial level. Only three characteristics of the respondents shown in Table 15 exhibited significant moderating effects, namely: 1) gender, 2) being employed by an organisation in an initial stage of AI implementation, and 3) being employed by a company where AI is either not implemented or the respondent was not aware of the stage of AI implementation. The results with significant moderation effects are shown in Table 15, with the last entry being marginal to the significance threshold.

Table 15. Summary of statistical testing for categorical variable moderation

Item	*R^2*	*Path moderated*	*B*	*Std.Dev.*	*T-statistic*	*P-value*	*Results*
Without moderation	0.554						
Gender	0.570	EAaff -> BRuse	-0.165	0.082	2.022	0.022	Significant: Effect is stronger in females
Stage of AI implementation: Initial stage	0.595	EAcog -> BRuse	-0.331	0.138	2.391	0.008	Significant: Effect is stronger in non-initial stages
Stage of AI implementation: AI not implemented or no awareness of implementation	0.595	EAcog -> BRuse	0.353	0.152	2.320	0.010	Significant: Effect is stronger in those whose company has not implemented AI or who do not have awareness of AI implementation intentions
Stage of AI implementation: AI not implemented or no awareness of implementation	0.595	EAaff -> BRuse	-0.262	0.155	1.689	0.046	Significant: Effect is stronger in those whose company has either operationalised AI or is intending to implement it

The graphs of the moderating effect are shown in Figure 9. Figure 9a demonstrates the moderating effect of gender on interaction between EAaff and BRuse. Since female gender was codes as 0 and male as 1, the negative beta indicates that in females the moderating effect is expressed stronger than in males: namely, the affective attitude towards AI has a stronger effect on the intent to use the organisational AI.

For the employees from the organisations where AI is not in initial roll-out stages of implementation, there is stronger interaction between the cognitive attitude towards AI and the intention to use it (Figure 9b). Figure 9c shows that the impact of employee cognitive attitude towards his/her intention to use AI is stronger in companies which have not yet implemented AI or where the employee is not aware of its implementation. As can be seen from Figure 9d, the relationship between EAaff and BRuse is more pronounced in those whose company has either operationalised AI or is intending to implement it.

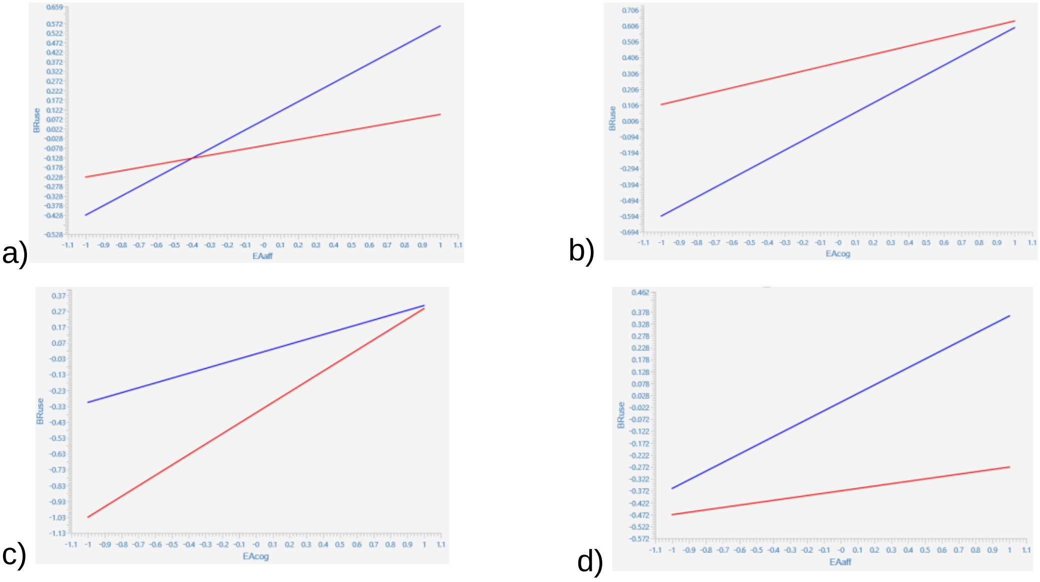

Figure 9. Slope analysis graphs for the moderating effect of categorical characteristics: a) gender on interaction between EAaff and BRuse, b) initial stage of AI implementation on interaction between EAcog and BRuse, c) not implemented/ not awareness of AI implementation on interaction between EAcog and BRuse; d) AI is operationalised or in initial stages of being implemented on interaction between EAaff and BRuse.
Blue line signifies low level of COnrm, red line – high level

5.4.3 Explanatory power of the model

The explanatory power of the model was assessed using three measures: R^2, f^2 and Q^2 (Hair et al., 2019b). The results are shown in Table 16. Using the R^2 measure, and the thresholds of 0.75 for substantial, 0.50 for moderate and 0.25 for weak power, suggested by Hair et al. (2019b), the model showed moderate explanatory power for EAaff and BRuse, while the BRlea and EAcog are weak. As per Cohen (1988), who used a threshold of 0.26 for substantial explanatory power, all the endogenous constructs satisfy this rule except COnrm affected by POS, which was slightly lower than the suggested threshold (0.24).

Table 16. Results of assessing explanatory power of the model

Predictor	***Outcome***	R^2	f^2	Q^2
EAaff	BRlea	0.384	0.022	0.238
EAcog			0.091	
EAaff	BRuse	0.568	0.080	0.340
EAcog			0.175	
POS	COnrm	0.241	0.318	0.225
AO	EAaff	0.528	0.385	0.496
CC			0.038	
EK			0.075	
OC			0.038	
AO	EAcog	0.478	0.421	0.444
CC			0.011	
EK			0.018	
OC			0.058	

The magnitude of the relationships between the latent variables expressed via the effect size f^2 showed a range of levels, from small (0.011 for CC –> EAcog) to high

(0.421 for AO –> EAcog). The majority of the constructs had values above the threshold of 0.02 (Cohen, 1988), indicating a good explanatory power of the model.

The Q^2 values for all endogenous constructs were positive and considerably higher than a threshold of 0.0 (Hair et al., 2019b), also contributing to a conclusion that the model overall had a strong degree of relevance.

5.4.4 Predictive power of the model

To assess the predictive power of the model, the Q^2predict values were analysed first. They all showed positive values with significance (Table 17). Further to this, RMSE was used as the distributions of prediction errors for different variables appeared symmetric. 83% of the endogenous latent variables satisfied the criteria to rank the model on the medium – high side of the predictive power, with medium at 50%, and high at 100% (Hair et al., 2019b). The constructs on the lower end of the predictive ability in the model were the intent to leave the organisation, and normative commitment. Employee's affective and cognitive attitudes were predicted effectively, as well as the intent to use the organisational AI. As recommended by Hair et al. (2019b), the results of the PLSpredict should be focused on the key endogenous constructs in the model. Such variables in the model were BRlea and BRuse, shown in bold font in Table 17.

Table 17. Results of assessing predictive power of the model

Item	*Q²predict*	*PLS-SEM_RMSE*	*LM_RMSE*	*Flagging where PLS-SEM RMSE < LM RMSE*
BRlea1	**0.146**	**0.732**	**0.756**	**1**
BRlea2	**0.154**	**0.778**	**0.813**	**1**
BRlea3	**0.220**	**0.728**	**0.726**	**0**
BRlea4	**0.090**	**0.852**	**0.834**	**0**
BRuse1	**0.328**	**0.750**	**0.790**	**1**
BRuse2	**0.252**	**0.699**	**0.717**	**1**
BRuse3	**0.336**	**0.763**	**0.774**	**1**
COnrm1	0.096	1.155	1.175	1
COnrm2	0.070	1.111	1.125	1
COnrm3	0.098	1.157	1.182	1
COnrm4	0.215	1.070	1.061	0
COnrm5	0.097	1.126	1.191	1
COnrm6	0.196	1.050	1.109	1
EAaff1	0.482	0.634	0.666	1
EAaff2	0.432	0.647	0.681	1
EAcog1	0.404	0.591	0.615	1
EAcog2	0.378	0.689	0.738	1
EAcog3	0.356	0.594	0.599	1
Percentage of items where PLS-SEM RMSE < LM RMSE			83%	

5.5 Conclusion

The chapter provided details of the statistical analysis conducted on the results of the survey. Descriptive statistics gave an overview of the respondents profile. The measurement model was tested first, following a two-stage disjoint approach.

In the first stage, all single-order and LOCs were tested for reliability and validity. In the second stage, the HOCs were tested. A number of iterations on reliability and validity testing were performed in the first stage, which resulted in elimination of a few items, such as POS7, POS8, COcnt2, COcnt3, COcnt5 and EAaff3. The resulting measurement model showed good reliability and validity. A construct that exhibited problems through different stages of the model testing was the commitment to organisation, specifically the continuity commitment dimension of it. This construct was closely monitored through the process.

In the second stage of the measurement model testing, no collinearity was observed. The assessment of the significance and relevance of outer weights and out loadings, however, showed problems with COcnt dimension of the CO construct, measuring the opposite of the construct. This dimension was removed going forward. Overall, the measurement model showed acceptable quality to be used in further structural model testing.

During the assessment of the structural model, all the direct relationship hypotheses were found to be confirmed at a significance p-value level of 0.05, except one, CC –> EAcog. In addition, a non-hypothesised relation has been found significant, a positive correlation between POS and CO. The indirect relationships as hypothesised have not been confirmed. Bearing in mind that the CO construct exhibited problems through the study, it was decided to test its individual dimensions in the model. The COnrm dimension had significant results in the structural model (shown in Figure 6). There is full mediation from POS to EAcog – BRlea and EAaff – BRlea via COnrm.

A number of demographic variables effects were tested on the model as well. Three elements were found to have significant moderating effects: gender on EAaff - BRuse, and stage of AI implementation on EAcog – BRuse. In addition, predictive and explanatory power of the model have shown to be good.

6 DESCRIPTION OF RESULTS

6.1 Introduction

The current study investigated the employees appraisal of AI and its relationship with such behavioral outcomes as intention to use the organisational AI or to leave the company. The model proposed by Chiu et al. (2021) found empirical support. In addition, influence of different moderating variables was tested to understand their influences on the employee inclination to use the organisational AI or to leave the organisation if AI is implemented.

The results of the statistical analyses were presented in the previous chapter. To shed some light on the implications of the statistical findings, the results are further explored in this chapter. The chapter is structured as follows: first, the results of the direct relationships in the model are discussed, followed by some insights into indirect relationships. The final model is shown in Figure 10.

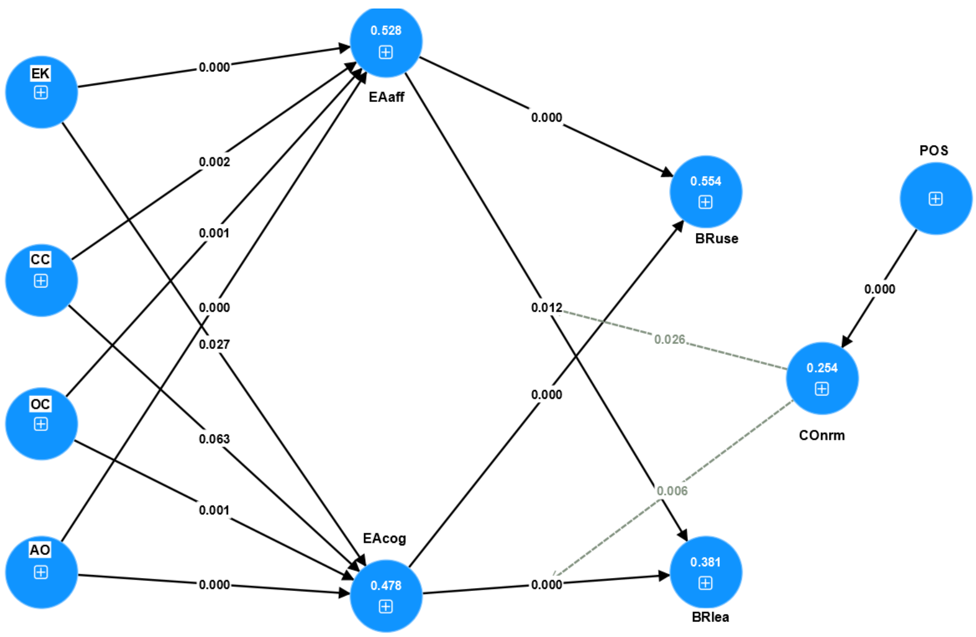

Figure 10. Final model of employee appraisal of AI. The p-values are shown on the paths

6.2 Model direct relationships

6.2.1 Appraisal and employee attitude constructs association

6.2.1.1 Association of employee subjective knowledge of AI and employee attitudes towards AI

H1a. Employee knowledge of AI is positively associated with affective attitude toward AI.

H1b. Employee knowledge of AI is positively associated with cognitive attitude toward AI.

The subjective knowledge serves as a proxy for the employee's objective knowledge (Carlson et al., 2008). The previous study by Chiu et al. (2021) did not find an empirical support for these two hypotheses, producing β of 0.08 for EK – EAaff and 0.09 for EK – EAcog. The justification by the authors was due to a moderate correlation and complex relationship between objective and subjective knowledge exacerbated by the complexity of the AI concept being measured, and an indirect impact of knowledge on the employee attitudes. In the current study, the two hypotheses were confirmed, with β coefficients of 0.208 and 0.106 correspondingly (Table 11). It showed that there is a significant positive association between the employee subjective knowledge of AI and his/her attitudes toward AI, both affective and cognitive. The higher the employee perceives him/herself as knowledgeable about AI, the more likely he/she would experience a positive attitude toward the technology, treating it as a challenge rather than a stressor (Lazarus & Folkman, 1984). It has an important consideration for companies, motivating for investing resources in educating the staff about AI. While seemingly obvious, causality cannot be assumed in either of these relationships as it can be argued that high affective and cognitive attitudes towards AI can serve as an inspiration for a person to increase the understanding of AI, forming a meritorious cycle.

In addition, analysis of the statistics and histograms of the measurement items (Appendix 2.1) in the EK construct revealed close to normal, slightly negatively skewed distributions, indicative of the sample with a reasonable understanding of AI. However, an exception was the item EK3 which showed a positively skewed distribution. This is understandable as the question required the respondent to benchmark against peers and could be measuring a psyche of the person, sensitive to cultural background, rather than pure subjective knowledge of a subject.

6.2.1.2 Association of perceived cognitive capabilities of AI and employee attitudes towards AI

H2a. Cognitive capabilities of AI as perceived by an employee have a positive association with affective attitude toward AI.

H2b. Cognitive capabilities of AI as perceived by an employee have a positive association with cognitive attitude toward AI.

The employee appraisal of AI cognitive capabilities probed such aspects as context understanding, logic transparency and natural language understanding. The previous study by Chiu et al. (2021) found an empirical support for both relationships, CC – EAaff and CC - EAcog, to be significant and positive.

In the current study, the histograms of the items measuring the CC construct (Appendix 2.2) showed the distributions to be negatively skewed with a median of 4.0 and the mean values varying between 3.4 and 4.1. It reflected an overall high perception of the AI cognitive capabilities by the respondents. A similar picture was exhibited by the employee affective and cognitive attitudes constructs towards AI, implying favourable attitudes, with mean values 3.8-4.0 for affective attitude and 4.0-4.1 for cognitive attitude (Appendix 2.5).

While the perception of high cognitive capabilities of AI in the current study was significantly related with positive affective attitude towards the technology, it did not show a significant relationship with employee cognitive attitude toward AI (albeit only marginally, at a p-value of 0.063 being higher than the accepted probability threshold of 0.05). This finding might be indicative that in spite of the fact that on a rational level an individual might be appraising the cognitive capabilities of AI as high, when regarding the adoption of AI at work, he/she has some reservations that such a decision might not be unequivocally valuable, beneficial or wise. These reservations might not be unreasonable, since Homo Sapiens have developed cognitive processes that enable them to determine harmful or threatening experiences and adapt for survival and well-being (Lazarus & Folkman, 1984).

6.2.1.3 Association of perceived operational capabilities of AI and employee attitudes towards AI

H3a. Operational capabilities of AI as perceived by an employee have a positive association with affective attitude toward AI.

H3b. Operational capabilities of AI as perceived by an employee have a positive association with cognitive attitude toward AI.

The perceived operational capabilities of AI included reliability, flexibility and integrability. The extant literature findings (Chiu et al., 2021) obtained strong β coefficients of 0.36 and 0.41 respectively.

Analogous to perceived cognitive capabilities of AI in the current study, all the measured items of the OC construct displayed negatively skewed distributions (Appendix 2.3), with mean values of 3.6-4.2 indicative of favourable perceptions of the AI operational capabilities amongst the sample. There has been a significant positive association found between the OC and both, affective and cognitive attitudes of an employee towards AI. The interaction of OC – EAaff exhibited the β of 0.196 and that one of OC – EAcog of 0.257. Similar to Chiu et al. (2021), the current research indicates that employees regard the operational capabilities of AI to be of higher value than cognitive capabilities.

6.2.1.4 Association of anticipated adverse outcomes of AI and employee attitudes towards AI

H4a. Anticipated adverse outcomes of AI as perceived by an employee have a negative association with his/her affective attitude toward AI.

H4b. Anticipated adverse outcomes of AI as perceived by an employee have a negative association with his/her cognitive attitude toward AI.

The formative HOC of anticipated adverse outcomes of AI comprised of job-related and humanity-related outcomes LOCs. The job-related outcomes probed the concern that implementation of AI could cause a change in job content, organisational decision-making process, and the employee's ability to handle the implemented AI. The humanity-related adverse outcomes dimension captured the employee's apprehension of the reduction in the number of jobs available for humans, reduced importance and perceived usefulness of the humans and the expectation of the de-humanisation of the workspace where the focus is on building relationships with machines rather than humans.

The study by Chiu et al. (2021) found a confirmation for AO – EAaff only, with $\beta =$ - 0.30. The absence of the theorised correlation was explained by the authors as pertaining to complexity of individuals, where controversial attitudes could co-exist in one individual.

As can be seen from Appendix 2.4, across the 216 responses, the three job-related items showed positively skewed distributions. It is apparent from the statistics that there is a less pronounced level of concern about the job content and the employee ability to handle AI, and medium concern about the change in decision-making process. Among the humanity-related items, the concern about the tendency to form relationships with machines rather than humans was the most distinct with a negatively skewed distribution, while the availability of fewer jobs and human usefulness in the workplace did not reveal itself as a considerable stressor.

The relationship of the anticipated adverse outcomes construct with both, affective and cognitive attitudes, showed to be negative and significant, with β coefficients of -0.453 and -0.498 respectively, the latter contradicting the previous study findings. The successful empirical results of the current study point towards a more coherent phenomenon between the expectation of adverse outcomes in the individuals and employee attitudes. Based on the analysis of the histograms in Appendices 2.4 and 2.5, the tendency across the respondents was to consider the adverse outcomes as low or mild, while the affective and cognitive attitudes erred on the positive side. The cognitive appraisal process consists of evaluating an event with regards to its significance to the well-being and the extent to which it is considered as irrelevant, benign-positive or as a stressor by an individual (Lazarus & Folkman, 1984). It shows that overall, the individuals in the sample tended to consider AI as a challenger and a benign-positive event rather than a stressor, adding support to the appraisal model.

6.2.2 Employee attitudes towards AI and behavioral outcomes association

6.2.2.1 Employee attitude toward AI and intention to use enterprise AI

H5a. Employee affective attitude toward AI is positively associated with intention to use enterprise AI.

H6a. Employee cognitive attitude toward AI is positively associated with intention to use enterprise AI.

The sample of respondents exhibited a strong inclination to use the organisational AI, with negatively skewed distributions, the median of 4.0 and the mean values of 4.0-4.2 (Appendix 2.6). There are significant positive relationships between the employee affective and cognitive attitudes towards AI and intention to use AI, with β coefficients of 0.308 and 0.495 (Table 11) correspondingly. This confirmed the finding that the current sample of respondents tended to consider AI as a challenge rather than a threat. The challenge appraisal allows to focus the efforts on a potential for growth and is accompanied by excitement and eagerness (Lazarus & Folkman, 1984). The previous study by Chiu et al. (2019) showed similar relationships albeit of lower strength: 0.20 and 0.44 for the two paths.

6.2.2.2 Employee attitude toward AI and intention to leave organisation

H5b. Employee affective attitude toward AI is negatively associated with intention to leave the organisation if AI is implemented

H6b. Employee cognitive attitude toward AI is negatively associated with intention to leave the organisation if AI is implemented.

In the preceding study by Chiu et al. (2021), only the affective attitude has been found to have a significant effect on the intent to leave, with $\beta =$ -0.19. The authors explained it by a presence of an extreme emotional response to cope with the AI as a stressor, which was not as pronounced for the cognitive attitude.

In the current study, the relationship for both, affective and cognitive attitudes with the intent to leave was negative and significant, with β of -0.206 and -0.364. All the items measuring the intention to leave the organisation in case of AI implementation exhibited strongly positive distributions with medians of 1.0-2.0 and mean values of 1.6-2.0 (Appendix 2.7), indicative of the prevailing intent to stay with the company that implements AI, as an employee emotional response and a cognitive reasoning.

6.2.3 <u>Perceived organisational support and commitment to organisation</u>

A relationship between POS and CO which has not been framed at the commencement of the study in a separate hypothesis proved to be significant and positive, with β = 0.673. Similar findings have been reported by different authors previously. Pattnaik, Mishra & Tripathy (2020) performed a study on 430 corporate managers from junior to senior level across manufacturing companies in India and found a significant correlation between POS and CO. Arasanmi and Krishna (2019) explored the relationship among 134 employees of a local council in New Zealand, confirming a significant relationship between POS and CO with β coefficient of 0.513 and highlighting importance of employer branding as a facet of POS in improving the retention of the employees. Stan and Virga (2021) in their study of 400 Romanian teachers working in pre-tertiary education found that procedural justice and social support from colleagues and management resulted in increased commitment to the organisation. The current study finding confirmed a general need to nurture organisational support for the employees in order to improve their commitment, irrespective of any intent to implement AI.

6.3 Model indirect effects

6.3.1 <u>POS moderating effect on the employee attitudes – behavioral outcomes paths</u>

H7a. POS affects the relationship between affective attitude and intention to use AI such that the relationship is strengthened with perceived high level of organisational support.

H7b. POS affects the relationship between affective attitude and intention to leave the company such that the relationship is weakened with perceived high level of organisational support.

H7c. POS affects the relationship between cognitive attitude and intention to use AI such that the relationship is strengthened with perceived high level of organisational support.

H7d. POS affects the relationship between cognitive attitude and intention to leave the company such that the relationship is weakened with perceived high level of organisational support.

The indirect effect of POS on the paths between the employee attitudes to AI and intention to use it or to leave the company was tested in the study. Extant literature found support for similar relationships. For instance, a significant moderating effect of POS on the relationship between awareness of AI and robotics and turnover intentions was established by Li et al. (2019) among luxury hotel employees in China. The relationship was weakened when employees perceived a greater organisational support. The authors suggested that when employees recognised that their contribution was appreciated by the company, they tended to feel more enthusiastic and stay with the company. A study by Albalawi et al. (2019) investigated a mediated moderation from POS to CO to intention to leave the company, however, no attempt was made to understand if there was a significant effect from POS to the intention to leave the company. To the best of author's knowledge, none of the studies investigated a moderating effect from POS to the employee appraisal of AI and related behavioral intentions.

The moderating effects of POS on the relationships between the employee affective and cognitive attitudes and behavioral outcomes have not been supported in the current study. Explanation for it will be found in Section 6.4.1. What the reader is reminded of at this stage is that, as mentioned in Section 6.2.3, POS has been found to have a significant positive correlation to the employee commitment to organisation, irrelevant of any AI implementation context.

6.3.2 Mediated moderation by CO as a higher-order construct

H8a. CO mediates the moderating relationship of POS on affective attitude - intention to use AI.

H8b. CO mediates the moderating relationship of POS on affective attitude - intention to leave the organisation.

H8c. CO mediates the moderating relationship of POS on cognitive attitude - intention to use AI.

H8d. CO mediates the moderating relationship of POS on cognitive attitude - intention to leave the organisation.

The analysis has not confirmed any of the four hypothesised mediated moderation effects of the commitment to organisation HOC on the relationships between employee attitudes to AI and behavioral outcomes. Previous research by Arasanmi and Krishna (2019) revealed a mediation effect of CO in the POS - employee retention relationship. A similar mediating effect of CO on the employee turnover intention appeared in a study by Albalawi et al. (2019) among Jordanian SMEs workers. The latter used a similar measurement instrument operationalising the HOC of organisational commitment via the three LOCs, affective, continuance and normative. The 13-item measurement scale was borrowed from Ziauddin, Jam and Hijazi (2010) and formed a shortened version of the original 18-item measurement instrument suggested by Meyer et al. (1993). As such, there are differences in the adapted scales across studies. This might be one of the reasons behind non-performance of the hypotheses in the current study. Also, none of the mentioned studies investigated a mediated moderation effect from POS to the employee appraisal of technology and behavioral intentions, and, as such, no direct inferences can be made between the studies.

6.4 Post-hoc analysis

6.4.1 Mediated moderation by CO lower-order constructs

To test a suggestion proposed above, that the complexity of the commitment to organisation HOC obscures its possible mediating effect in the model, the three lower-order individual components of CO were tested one at a time. One of the three, namely, normative commitment to organisation was found to have a significant mediated moderation effect on two paths: EAaff – BRlea and EAcog – BRlea. Combined with the significance of the POS – COnrm path, this test suggested a presence of full mediation of POS on EAcog – BRlea and EAaff – BRlea, via COnrm.

At lower levels of COnrm there is a stronger effect on the path between employee affective attitude to AI (or absence thereof) and the intent to leave the company which implements AI (Figure 8). It means that if the employee does not experience a strong affinity towards AI in the workplace, the intention to leave the company will be stronger if he/she does not have normative commitment to the company. For the cognitive attitude of employee to AI and the intent to leave the organisation, the correlation is stronger at higher levels of normative commitment. In other words, when the employee has a good intellectual attitude towards AI, his/her intent to leave the company which is implementing AI will be reduced even further if he has strong normative commitment towards the firm.

An attempt to find an explanation of this phenomenon across previous studies pointed to a few possible reasons behind it. The first one is that different generations have different inclinations towards components of the commitment to organisation (Glazer et al., 2019; Costanza et al., 2012). As can be deducted from Table 3 with a precision of a few years, the GenX group represented about 58% of the surveyed respondents in the current study, while Millennials formed approximately 36%. Although the findings by Glazer et al. (2019) were not conclusive for the current research, the inferences by Costanza et al. (2012) do indicate to a possible reason behind a significant mediating effect of normative commitment to organisation, as GenX forms the majority of the surveyed group. It, however, warrants a need for further generational analysis of the mediating role of organisational commitment.

The multidimensional commitment to organisation was studies by Ahmad (2018) in an effort to understand the effect of reciprocity experienced by an employee in an exchange for organisational offering on his/her behavioral outcomes. One of the focuses of the study was to understand the relationship between affective, normative and continuance commitment on the intention to leave the company. It was found that among the three components of the CO, the highest impact was the normative commitment to the organisation, which was associated with the reciprocity the employee felt toward the organisation. The author emphasised that normative commitment should be paid attention to when assessing employees embeddedness (Ahmad, 2018).

6.4.2 Categorical variable moderation

Moderation by a number of demographic variables allowed to attain additional insights into factors important for understanding the AI cognitive appraisal behavioral outcomes. Two descriptor characteristics of the respondents were found to have significant moderating effects on the four paths between employee attitudes to AI and behavioral outcomes: gender and stage of AI implementation in the company. Testing for gender moderation revealed that affective attitude towards AI had a stronger effect on the intent to use the organisational AI in females. Testing for the stage of AI implementation in the company appeared rather interesting.

The stage-of-AI-implementation assessment comprised of two subtests. In the first one, the responses were divided into two groups. The first group consisted of those whose company entered the initial stage of AI implementation. The perceived uncertainty was deemed to be higher in this group. The second group included the rest of the respondents, from the employees whose organisations were not in initial roll-out stages of implementation. It would imply these employees belonged to the companies which did not have an intent to implement AI, the employees were completely unaware of the stage of AI implementation their company was in, or the AI has been implemented and operational. This group, arguably, was perceived to have a lower level of uncertainty associated with consequences of AI implementation in the workspace. The moderation test showed that the relationship between the employee cognitive attitude towards AI and the intent to use it was stronger in the second group. This is attributed to a lower level of perceived risk, such as job redundancy when the company implements AI, or when the company does not plan to implement AI. The event of AI implementation is either in a long-term future or employees have attained job security in companies with operationalised AI. If the level of perceived risk is higher, positive appraisal of AI will not necessarily translate into an intent to use the AI but might rather result in deterioration of work engagement.

The second subtest elaborated on the first one. Again, the responses were divided into two groups: 1) those where AI was not implemented or the employee did not have any awareness of AI implementation, and 2) the rest, namely, those where the company was in initial or advanced stage of implementation. This test revealed that the relationship between the employee cognitive attitude towards AI and the intention to use it was stronger in companies which have not yet implemented AI or where the employee was not aware of the company implementation intent. This can possibly be explained by the fact that such an employee does not have a library of personal experiences in the workplace to temper his cognitive appraisal of AI. Once he/she has been exposed to the process of AI implementation he/she might become disillusioned that AI provides a fast and magical solution as per initial appraisal.

6.5 Summary of findings

In summary of the findings presented above, the reader is referred to Table 18 below. The findings of the hypotheses relating to the cognitive appraisal model are compared to the previous research by Chiu et al. (2021) conducted for pre-adoptive stage of AI appraisal.

Table 18. Summary of findings relating to EAAIM and comparison to the previous study findings by Chiu et al. (2021)

Hypothesis ID	***Hypothesis***	***Previous research findings***	***Current research findings***
	Employee appraisal of AI – employee attitudes to AI		
1a	Employee subjective knowledge of AI is positively associated with affective attitude toward AI	Not supported	Supported
1b	Employee subjective knowledge of AI is positively associated with cognitive attitude toward AI	Not supported	Supported
2a	Perceived cognitive capabilities of AI have a positive association with affective attitude toward AI	Supported	Supported
2b	Perceived cognitive capabilities of AI have a positive association with cognitive attitude toward AI.	Supported	Not supported
3a	Perceived operational capabilities of AI have a positive association with affective attitude toward AI	Supported	Supported
3b	Perceived operational capabilities of AI have a positive association with cognitive attitude toward AI	Supported	Supported
4a	Anticipated adverse outcomes of AI have a negative association with affective attitude toward AI	Supported	Supported
4b	Anticipated adverse outcomes of AI have a negative association with cognitive attitude toward AI	Not supported	Supported
	Employee attitudes to AI – employee behavioral responses		
5a	Affective attitude toward AI is positively associated with intention to use enterprise AI	Supported	Supported
5b	Affective attitude toward AI is negatively associated with intention to leave the organisation if AI is implemented	Supported	Supported
6a	Cognitive attitude toward AI is positively associated with intention to use enterprise AI	Supported	Supported
6b	Cognitive attitude toward AI is negatively associated with intention to leave the organisation if AI is implemented	Not supported	Supported

Findings pertaining to the moderation and mediation outside of the cognitive appraisal model are presented in Table 19.

Table 19. Summary of findings relating to the indirect effects outside the EAAIM

Hypothesis ID	***Hypothesis***	***Current research findings***
	POS effect on the employee attitudes - behavioural outcomes paths	
7a	POS affects the relationship between affective attitude and intention to use AI such that the relationship is strengthened with perceived high level of organisational support	Not supported
7b	POS affects the relationship between affective attitude and intention to leave the company such that the relationship is weakened with perceived high level of organisational support	Not supported
7c	POS affects the relationship between cognitive attitude and intention to use AI such that the relationship is strengthened with perceived high level of organisational support	Not supported
7d	POS affects the relationship between cognitive attitude and intention to leave the company such that the relationship is weakened with perceived high level of organisational support	Not supported
	CO effect on the employee attitudes - behavioural outcomes paths	
8a	CO mediates the moderating relationship of POS on affective attitude - intention to use AI	Not supported
8b	CO mediates the moderating relationship of POS on affective attitude - intention to leave the organisation	Not supported
8c	CO mediates the moderating relationship of POS on cognitive attitude - intention to use AI	Not supported
8d	CO mediates the moderating relationship of POS on cognitive attitude - intention to leave the organisation	Not supported

The summary of findings from post-hoc analysis which have not been hypothesised at the inception are presented in Table 20.

Table 20. Summary of findings relating to the post-hoc analysis

Hypothesis ID	***Hypothesis***	***Current research findings***
	Indirect terms with COnrm	
POS -> COnrm	POS has positive effect on normative commitment to organisation	Significant
COnrm x EAaff -> BRlea	COnrm moderates the relationship between employee affective attitude to AI and intention to leave the company	Significant
COnrm x EAcog -> BRlea	COnrm moderates the relationship between employee cognitive attitude to AI and intention to leave the company	Significant
POS -> COnrm x EAaff -> BRlea	There is a full mediated moderation effect of POS on EAaff – BRlea path via COnrm	Significant
POS -> COnrm x EAcog -> BRlea	There is a full mediated moderation effect of POS on EAcog – BRlea path via COnrm	Significant
	Categorical variable moderation	
Gender x EAaff -> BRuse	Employee affective attitude towards AI has a stronger effect on the intent to use the organisational AI in females	Significant
Initial stage of AI implementation x EAcog -> BRuse	Correlation is stronger in non-initial stages of AI implementation	Significant
AI not implemented or no awareness of implementation x EAcog -> BRuse	Correlation is stronger in those whose company has not implemented AI or who do not have awareness of AI implementation intentions	Significant
AI not implemented or no awareness of implementation x EAaff -> BRuse	Significant: Effect is stronger in those whose company has either operationalised AI or is intending to implement it	Significant, albeit marginally

In addition to the above, EAAIM as related to AI implementation in a company (Chiu et al., 2021) can be ranked as having medium – high predictive ability.

6.6 Conclusion

The current chapter presented the description of the research results and compared them to the similar inferences from the previous studies. The cognitive appraisal theory originally proposed by Lazarus and Folkman (1984) and further adapted via EAAIM for pre-adoptive appraisal of AI in the workplace (Chiu et al., 2021) has been confirmed in its majority, except one hypothesis, namely, that there is significant association between perceived cognitive capabilities of AI and employee cognitive attitude toward AI. Newly proposed mediated moderation of POS via CO to the paths associating employee attitudes to AI and behavioral outcomes were not confirmed. Post-hoc testing revealed that there is a significant mediated moderation on the above-mentioned paths when normative commitment to organisation is isolated from the higher-order CO construct. In addition, categorical variable moderation by a number of respondents' descriptors was tested on the same four paths of the attitudes – behavioral responses and showed to have significance for gender, and stage of AI implementation in the company. The next chapter delves into conclusions stemming from the research.

7 CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

The current chapter presents conclusions of the study stemming from the Chapter 5 statistical analysis and Chapter 6 description of the results. Principal conclusions and contribution to the theory are followed by the implications for the management. The chapter concludes with the mentioning of the limitations and suggestions for future research.

7.2 Principal conclusions

7.2.1 EAAIM holds for employees at companies of different stages of AI implementation

EAAIM based on cognitive appraisal theory (Lazarus & Folkman, 1984) and developed for pre-adoptive stage of AI implementation in organisations (Chiu et al., 2021) has been tested across a sample of respondents in companies which undergo different stages of AI implementation. The model posits that employees go through a cognitive appraisal process of AI, which is influenced by the person's knowledge of AI, his/her believes in operational and cognitive capabilities of AI, and perception of adverse outcomes of AI on a personal job-related level and broader humanity-related level. It is important to consider both affective and cognitive appraisal elements of employee perceptions (Lazarus & Folkman, 1984; Chiu et al., 2021) as they lead to the employee intention to use the AI or to leave the company (Chiu et al., 2021), in its worst form. An overarching conclusion is that the model has been empirically confirmed to hold true for employees whose companies are in different stages of AI implementation. The stage of AI implementation serves as a moderator for the model. The model forms the basis of the hypotheses supported by the study with the principal conclusions summarised below.

7.2.2 Employee appraisal of AI includes constructs that have positive (EK, CC and OC constructs) as well as negative (AO construct) association with employee attitudes toward AI

The study looked at the appraisal of AI from an employee perspective. Three out of four employee appraisal constructs have been proven to have positive correlation with both, affective and cognitive attitudes of the employee towards AI. They are employee subjective knowledge of AI used as a proxy for objective knowledge, and perceived cognitive and operational capabilities of AI. One path did not exhibit a significant correlation, namely, between perceived cognitive capabilities and cognitive attitude to AI. For the other paths, the higher any of the three constructs factors, the more positive the employee emotional and intellectual attitudes to AI in the workplace.

The adverse outcomes of AI implementation have shown to have significant negative effect on the employee appraisal of AI. As suggested by Lazarus and Folkman (1984) in their landmark theory, it is important to approach the appraisal from a continuum of threat and challenge perspectives, as threat has a cognitive facet of personal harm and causes negative emotions, while challenge implies a sense of control and potential for growth and produces positive emotions. There is an important implication: different coping efforts need to be employed along the threat-challenge continuum (Lazarus and Folkman, 1984). The treatment of adverse outcomes as a higher-order construct separate from other appraisal elements allowed to consider it as a stressor in the model, thus avoiding incurring a-priori assumptions (Mazzola & Disselhorst, 2019) on the nature of AI appraisal by an employee as, in general, being a stressor or challenger.

Relation of a number of elements of the “dark” side of AI appraisal with the employee attitudes were explored in extant literature. Techno-overload was tested in a form of a moderator rather than another independent variable in the relationships between responsible AI justice and employee attitude to, satisfaction with and intentions to use AI (Wang et al., 2021). Braganza et al. (2021) alluded that in addition to two main types of psychological contract, relational and transactional, there was an emergence of a third type of psychological contract associated with AI implementation in workplace, which they termed “alienation” contract. While existence of the two conventional types of psychological contract in a workplace were positively related to employee engagement, the alienation contract had a negative effect (Braganza et al., 2021). The anticipated adverse outcomes of AI in a form of career and job threat showed to be negatively correlated with job embeddedness and career satisfaction, and positively related to turnover intent (Brougham & Haar, 2018). Support for a relationship between the employee comfort in technology usage and his/her long-term believes about the work and the perceived threat to one’s job due to the advancement of the Forth Industrial Revolution has been found by Nam (2019). The co-existence of both positive and negative sides of AI appraisal in the same employee, such as effort and performance expectancy has been found to lead towards differing behavioral intents by managers for decision-making (Cao et al., 2021). The positive attitudes termed intelligent-automation, emphasise convenience of automation and result in pragmatic and balanced perception of positive and negative implications of AI by an employee. On contrast, negative attitudes such as opposition to AI due to absence of human interaction may lead to a prevailingly concerned attitude even if the value-add is recognised by an employee.

7.2.3 Employee attitudes toward AI have positive association with the intention to use AI and negative association with the intention to leave the company implementing AI

The study confirmed that affective and cognitive attitudes of employees toward AI are positively correlated with the intent to use the technology and negatively correlated with the intent to leave the company. The effect of the perceived performance of the AI technology on the cognitive and emotional appraisal, further leading to an intent to use it, has been found among clients in service industry (Gursoy et al., 2019) and among employees of diverse industries in Taiwan (Chiu et al., 2021). In health care, a positive correlation between the perceived cognitive and operational capabilities of AI with the attitudes of employees to AI and their intent to use AI have been established by Wang et al. (2021). The extant literature findings mentioned in the preceding section also support the conclusion of this section albeit differing in moderators (Wang et al., 2021; Braganza et al., 2021; Brougham & Haar, 2018).

7.2.4 Mediated moderation effect from POS to attitudes – behavioral responses paths via CO

Previous studies (Brougham & Haar, 2018; Li et al., 2019) indicated that POS was an important moderator of employee AI awareness and turnover intention. On the other hand, CO was found to mediate the relationship between POS and turnover intention (Arasanmi & Krishna, 2019), and between HPWP such as performance appraisal, compensation, and employment security and turnover intentions (Nasurdin et al., 2018). A mediated moderation effect from POS to the path between employee attitudes and behavior, via employee commitment to the organisation was previously confirmed in the extant research (Arfat & Riyaz, 2013; Ahmad, 2018).

The current study did not establish a hypothesised mediated moderation effect of POS on the attitudes – behavioral responses path via CO, when the higher-order construct of CO was considered in its original proposed form (Meyer et al., 1993).

While, usually, the level of employee engagement in the workplace is positively correlated with the level of agreeability of the psychological contract between him/her and the organisation, adoption of AI in a company often results in a creation of an alienation psychological contract (Braganza et al., 2021). This points toward a complex nature of the mediating role of the employee commitment to organisation. Adopting the formative HOC of organisational commitment in its entirety does not fit the complexity of the phenomenon, motivating for a disintegrated approach to test the mediating influence of each LOC on the relationships. Conducting this analysis showed that only normative commitment to organisation revealed significant fully-mediated moderation of POS on a the EAaff – BRlea and EAcog - BRlea. A further support for this finding might be stemming from a suggestion by Lazarus and Folkman (1984) that the appraisal process is influenced by the commitment and beliefs, which points towards normative roots of commitment.

7.2.5 Presence of moderation effect of stage of AI implementation

Due to the fact that understanding people's attitudes towards AI is becoming more and more important, the study has been extended beyond the testing of originally proposed hypotheses, in order to extract additional empirical insight on the moderating effect of the stage of AI implementation in the company. The following moderating effects have been found:

For the path between employee cognitive attitude to AI and intention to use AI, two groups of employees have shown a stronger moderating effect: 1) the one who was in non-initial stage of AI implementation, and 2) the one whose company has not yet implemented AI (or the employee was not aware of the AI implementation intentions). The absolute value of the β coefficient for the first group was 0.331 and for the second one 0.353. Taking into consideration that the first group contained the second one, a conclusion can be drawn that the most pronounced moderating effect on the EAcog – BRuse path is exhibited by those whose company has not yet adopted AI (or the employee is ignorant about the stage of implementation). The possible explanation of this phenomenon is that such employees do not have the first-hand experience with AI in workplace. Once he/she has been exposed to the process of AI implementation the employee might become disillusioned that AI provides a fast and magical solution as per initial appraisal. A similar but weaker moderating effect has been found to exist for this group of employees (in no-implementation/no-awareness group) on the affective attitude – intention to use AI, with a similar explanation.

For employees of the companies in the initial stages of AI implementation, high cognitive appraisal of benefits associated with AI usage did not translate into an intent to use the system at work. This can be explained by a feeling of increased uncertainty. As suggested by Lazarus and Folkman (1984), the appraisal of a phenomenon is inversely related to its perceived ambiguity, due to a feeling of being out of control.

7.3 Theoretical contribution

The current research's main theoretical contribution is in gaining empirical support for the cognitive appraisal model: in understanding the AI appraisal process from an employee's perspective, affecting both cognitive and affective attitudes and leading to intention to use AI or to leave the organisation where AI is being implemented. Although the technology is expected to result in many positive outcomes for organisations and workforce, there are adverse effects and dark side to it that employees are concerned with. EAAIM (Chiu et al., 2021) has been found to have good explanatory and predictive power.

Among all the appraisal factors in the model, such as employee subjective knowledge of AI, perceived cognitive, perceived operational capabilities of AI and anticipated adverse outcomes of AI, the highest impact on the attitudes was from the adverse outcomes of AI. The highest absolute value of standardised regression coefficient β affecting the employee attitudes was found to pertain to AO -> EAcog (-0.498), followed by AO -> EAaff (-0.453) (Table 11). The current study also confirmed the negative association of AO with both affective and cognitive attitude for the first time, as in the previous study no support for cognitive attitude has been found (Chiu et al., 2021).

The positive association of the employee subjective knowledge and his/her attitudes to AI has been confirmed for the first time, while the previous study by Chiu et al. (2021) did not establish significance in these relationships. Analysis of the employee subjective knowledge measurement items distributions (Appendix 2.1) showed that EK3 was rather positively skewed while the other four were negatively skewed. This item does not purely reflect the degree of subjective knowledge of AI, but rather introduces an element of arrogance, which would be in conflict to humility characterising Eastern culture, important when considering the context in which the study by Chiu et al. (2021) took place. This might be the reason why the previous study did not support hypothesised relationships involving EK.

In addition, the research has not been confined to a certain stage of AI implementation. 40% of the respondents reported no organisational intent of implementing AI or non-awareness of the stage, 43% were in an initial stage of AI implementation and 17% reported an advanced stage where AI was operationalised. There has been an empirical support found for the cognitive appraisal model, across the companies at different stages of AI implementation, with the stage of implementation having a moderating effect on the employee appraisal of AI. This contributes towards generalisability of the model to the staff of the companies in different stages of AI implementation.

To follow the suggestion by the previous researchers who conducted the study in Taiwan (Chiu et al., 2021), the study has been extended into a cultural context which differs across dimensions suggested by Hofstede (1980) such as power distance, uncertainty avoidance, the level of collectivism, masculinity and long-term orientation. This, presumably, helped to find support for two previously non-significant relationships in the model.

Decomposing the HOC of organisational commitment into its dimensions of affective, cognitive and normative commitment and testing each one's mediating moderation effect showed significant effect on the model for the normative commitment only. A need to decompose a complex higher-order CO construct into its constituents might be indicative of an increasing level of complexity in the post-Covid-19 world, as well as a complex nature of the AI phenomenon. In summary, the reported results confirmed the theory, and possibly led to new hypotheses that can be posed for new studies.

7.4 Implications for management and other relevant stakeholders

This study confirmed a need to consider different practical implications when implementing AI solutions (Chiu et al., 2021). As firms compete in the race to improve performance and stay competitive by adopting automation (Frey & Osborne, 2017), an issue of successful implementation of AI technologies in workplace emerge. While a successful AI implementation is natural in companies which are born digital, it can pose considerable challenges when applied to incumbents (McAfee & Bryniolfsson, 2012). Some of the more straight-forward challenges are associated with a need to identify the layers of the workforce most susceptible to becoming redundant and reskill those employees into less susceptible domains (Frey & Osborne, 2017).

More subtle implications, however, relate to a need to understand the complexity in the employee appraisal of the technology, which can lead to different behavioral outcomes such as intentions to use or detach from the AI, and different levels of job embeddedness. An anticipation of adverse outcomes of AI by an employee is shown to lead to a negative appraisal of AI, which can result in lower employee engagement at work, and ultimately in an intent to leave the company. Better manager understanding of the AI appraisal process can help raise the employee appraisal of AI and to design interventions programs to increase the employees' knowledge about AI, educate them in operational and cognitive capabilities of AI and reduce negative perceptions of employees about AI. All these will result in an improved employee attitudes towards AI. The anticipated adverse outcomes can also be reduced by ensuring transparency and predictability of the AI systems.

Existence of both positive and negative appraisals by the same individual (Lichtenthaler, 2020) necessitates a need to gain an in-depth understanding of the roots of the negative attitudes with proper strategies to reduce them. It has implications for championing the employees with prevailing balanced attitude to AI and placing an appropriate emphasis during the hiring process (Lichtenthaler, 2020).

These behavioral outcomes are influenced by the organisational support the employee believes exists from the company and organisational commitment which can be a result of antecedents both within and outside the power of the organisation. Considering the factors within the control of the company, management can focus on tangible and intangible elements of organisational support. Tangible elements comprise such tools as competitive compensation, promotional policies and working conditions (Ahmad, 2018). One of the important intangible elements is improving the psychological contract with the employees (Nam, 2019). Psychological contract is one of the ingredients of perceived organisational support and can translate into employee higher normative commitment to the organisation, due to a feeling of reciprocity. The perceived organisational support can be also improved with the employer's branding (Arasanmi & Krishna, 2019), however, branding should represent a truthful reflection of the reality and be aligned with the factual situation of the provided organisational support not to undermine the employee trust in the company. In addition, to reduce the employee uncertainty associated with the implementation stage of AI, employers can undertake change management programs in-advance, involving employees in the new job-design process, and improving communication (Keim et al., 2014; Nam, 2019).

The process of appraisal is not static but evolves depending on the environment, availability of personal and organisational resources, adaptation of employee coping mechanisms (Lazarus & Folkman, 1984) and organisational support available (Arasanmi & Krishna, 2019). When adaptation occurs, it allows to transform the perception of an encounter from a threat to a challenge perspective leading to higher employee confidence and lowered feeling of emotional overwhelm (Lazarus & Folkman, 1984). Organisational efforts should be directed towards turning the AI implementation event from being perceived as a stressor to a challenger, by changing the employee perception of personal and organisational resources available, reducing the level of perceived uncertainty, improving the perceptions about the organisational AI and dispelling myths about it.

7.5 Limitations of the research

In addition to the methodological limitations mentioned in Section 4.8, the current research made use of a limited number of moderators. It would be beneficial to conduct a more comprehensive moderating analysis, specifically taking into consideration the peculiarities of the mediated moderation by the commitment to organisation. Although it was stipulated in the questionnaire that the commitment to organisation had to be considered with all other factors fixed, and the only condition being the implementation of the AI, a possibility exists that subdued economic conditions in post-Covid-19 world had a play on the answers regarding the commitment to organisation. In an environment of economic recession, extrinsic working conditions have a stronger influence on employee attitudes than intrinsic factors (Ahmed, 2018).

The population comprised of skilled employees and management of different levels in South Africa. Although a moderation by this variable did not show any significant effect on the model, further testing would be beneficial to benchmark the management level across industries. In addition, there are generational differences that might have influenced the tested model relationships. The study did not attempt to gain insight in these.

7.6 Suggestions for future research

Further investigation can add dimension to the model of cognitive appraisal. More detailed research into the generational differences will allow to refine the model. The study was conducted with the majority of responses collected from employees at different management level or skilled worker category. A further insight into differences across the job level hierarchy will allow to better tailor mitigation interventions for the workforce. Exploring a wider range of factors that moderate AI usage or disengagement intentions, such as types and qualities of AI systems and the alignment of their purpose with the organisational objectives (Dwivedi et al., 2021; Wang et al., 2021) can be beneficial.

The research questionnaire survey was used with hardly any adaptations from the previous research. There might be a need to consider a review of the different scales to better comply with reflective/formative principles, and to mitigate for ambiguity that can become pronounced across different cultures.

As mentioned above and brought about by different authors (Wang et al., 2021; Chiu et al., 2021), longitudinal research is needed to understand the evolvement of the employee appraisal of and engagement with AI along his/her journey with the company in AI implementation process. An area of interest in such research would be to investigate the change in psychological contract (Braganza et al., 2021).

The measurement instruments used for moderation analysis in the study have been found to cause some issues when undertaking the model assessment, necessitating elimination of a few items. In addition, two of the LOCs comprising the commitment to organisation, COaff and COcnt, exhibited absence of moderation on the model. Moreover, COcnt dimension showed to measure the opposite of the CO construct. Furthermore, only COnrm dimension had a moderating effect on the model. Taking into consideration that at the moment of conducting the research, the measurement instruments for POS and CO (Eisenberger, Huntington, Hutchison and Sowa, 1986; Meyer et al., 1993) have been around for a while, there is a need to revisit them as generational perceptions of what comprises a good organisational support or what would cause an employee to exhibit high affective or continuance commitment have changed.

Another reason that COnrm construct came across with a significant effect in the model can be due to the influence of personal factors. Lazarus and Folkman (1984) suggested that among important personal factors that influence cognitive appraisal of a situation as a challenge or a threat are commitments and beliefs, due to their ability to influence the choices, motivate, and evoke emotions. Introducing measurement items to capture personal commitments and beliefs (Lazarus & Folkman, 1984) will improve the understanding of the moderating factors in the model.

Another consideration for future research is to carefully consider questionnaires developed in the Western culture before adopting them to the Eastern. Introducing measurement items to capture cultural dimensions (Hofstede, 1980), in this and similar studies, will be beneficial in future.

7.7 Conclusion

Over the last decade, the advancement of AI in workplace and in personal lives has triggered different responses in humans. Due to a pressing need for the companies to understand the implications and consequences of the adoption of AI for the workforce, the cognitive appraisal theory and its EAAIM application to the appraisal process of AI in workplace have been explored in the research. The main focus of the study aimed at understanding the connection between the employee appraisal of AI, their attitudes and intention to use the AI or leave the company implementing it. This technology serves as a major source of stress and, as such, can result in reduced performance and turnover among the labour force (Lazarus & Folkman, 1984). The findings of the study contribute to a better understanding of the factors driving the AI appraisal and contain some recommendations for managers to prepare for the shift to AI-augmented workplace.

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APPENDICES

Appendix 1. Survey questionnaire

1.1 General information

Question		***Answers***	***Variable name***
1.	Age	Free-entry box	G01
2.	Gender	Male Female Prefer not to say Other	G02
3.	Country of residence	Free-entry box	G03
4.	Highest education level achieved (artisan)	High school Undergraduate qualification Undergraduate degree (Bachelors or Honours) Postgraduate degree or qualification Other	G04
5.	Type of degree	Technical (related to science, technology, engineering or mathematics) Non-technical (relying on soft skills)	G05
6.	Years' work experience	Free-entry box	G06
7.	Current employment status	Full-time Part-time Casual Self-employed Retired Other	G07
8.	Sector	Financial services and banking Mining and energy Agriculture, fishing and forestry Public sector Education Technology and telecommunications Construction Consulting Insurance Manufacturing and production Healthcare and medical Human Capital Advertising Security Arts and media Food and beverages Legal Transportation Other	G08
9.	Job type	Management, strategy and financial Computer, engineering, and science Services Sales and related Office and administrative support Installation, maintenance, and repair	G09

	Transportation and material moving Technical Other	
10. The most important characteristics of your job	• Assisting and caring for others	G10_care
	• Fine arts	G10_arts
	• Originality and creativity	G10_orig
	• Manual dexterity (ability to accurately execute certain movements)	G10_dext
	• Ability to work in cramped spaces	G10_cram
	• Specialised knowledge	G10_spec
	• Repeated works	G10_repeat
	• Interpersonal communication and coordination	G10_comm
11. Your management level	1. Unskilled worker 2. Semi-skilled worker 3. Skilled worker/supervisor who decides what has to be done, while following processes and procedures 4. Middle manager with ability to optimise resources through decision-making 5. Senior manager with cross-functional coordination 6. Top manager who sets the strategy and goals of the company 7. Other	G11
12. Are you a technology creator or a technology user? It can be industrial, electronic, mechanical, medical or communications technology types	• I am a user of technology • I avoid using technology • I create technology • Other	G12
13. Stage of AI implementation in your company	• No intent of implementing • Initial stages of AI implementation • AI is implemented and operational • I am not sure • Other	G13
14. My company relies on non-digital data in its value chain	1 - To some extent … 5 – To large extent	G14

1.2 Appraisal measurement instrument

Construct and source	***Dimension***	***Measurement item***	
Employee subjective knowledge of AI (Flynn & Goldsmith, 1999; Chiu et al., 2021)	Subjective knowledge	I know pretty much about AI	EK1
		I do not feel very knowledgeable about AI (reverse-coded)	EK2
		Among my circle of friends, I'm one of the "experts" on AI	EK3
		Compared to most other people, I know less about AI (reverse-coded)	EK4
		When it comes to AI, I really don't know a lot (reverse-coded)	EK5
Perceived cognitive capabilities of AI (Chiu et al., 2021; Srinivasan, 2016)	Context understanding	I think the AI system could handle contextual ambiguity.	CCcxt1
		I think the AI system could understand specific jargons and slangs	CCcxt2
		I think the AI system could learn new knowledge to understand a specific context	CCcxt3
	Logic transparency	I think the AI system would have clear logic	CClog1
		I think the AI system would use comprehensive logic	CClog2
		I think it is possible to improve and adjust the AI system's logic	CClog3
	Natural language understanding	I think the AI system could process languages and texts like a human	CClng1
		I think the AI system could understand jargons and terminologies from different industries	CClng2
		I think the AI system could understand the underlying meaning through languages and text	CClng3
Perceived operational capabilities of AI (Chiu et al., 2021; Nelson et al., 2005)	Reliability	I think the AI system would operate reliably	OCrel1
		I think the AI system would perform reliably	OCrel2
		I think the operation of the AI system would be dependable	OCrel3
	Flexibility	I think the AI system could be adapted to meet a variety of needs	OCflx1
		I think the AI system could flexibly adjust to new demands or conditions	OCflx2
		I think the AI system could be versatile in addressing needs as they arise	OCflx3
	Integrability	I think the AI system could effectively integrate data from different areas of the company	OCint1
		I think the AI system could pull together information that used to come from different places in the company	OCint2
		I think the AI system could effectively combine data from different areas of the company	OCint3

Anticipated adverse outcomes of AI	Job-related (Chiu et al., 2021)	I am concerned about the change in my job content	AOjob1
		I am concerned about the change in decision-making approach	AOjob2
		I am worried about that I may not be able to handle the AI system	AOjob3
	Humanity-related (Chiu et al., 2021; Jiang, Muhanna & Klein, 2000)	I am concerned about that there will be fewer jobs for humans	AOhum1
		I am concerned about the tendency to build relationship with machines more than humans	AOhum2
		I'm concerned that it makes human beings less important and useful	AOhum3

1.3 Attitudes measurement instrument

Construct	***Dimension and source***	***Measurement item***	***Variables***
	My attitudes towards using AI at work:		
Attitudes	Affective attitude toward AI (Chiu et al., 2021; Yang & Yoo, 2004)	My attitude towards AI is:	
		Annoyed (1) – Happy (5)	EAaff1
		Negative (1) – Positive (5)	EAaff2
		Bad (1) – Good (5)	EAaff3
	Cognitive attitude toward AI (Chiu et al., 2021; Yang & Yoo, 2004)	I consider adoption of AI as:	
		Foolish (1) – Wise (5)	EAcog1
		Harmful (1) – Beneficial (5)	EAcog2
		Worthless (1) – Valuable (5)	EAcog3

1.4 Behavioural measurement instrument

Construct	***Dimension and source***	***Measurement item***	***Variable***
Behavioural responses	Intention to use enterprise AI (Teo, 2011; Chiu et al., 2021)	I intend to use the AI system in the future	BRuse1
		I expect that I would use the AI system in the future	BRuse2
		I plan to use the AI system in the future	BRuse3
	Intention to leave organisation (Shore & Martin, 1989; Chiu et al., 2021)	53. If AI is implemented in my organisation, I would 1 - definitely not leave 2 - probably not leave 3 - uncertain 4 - probably leave 5 - definitely leave	BRlea1
		54. If AI is introduced, I would 1 - immediately plan to leave 2 - seriously consider leaving 3 - no feelings 4 - intend to stay 5 - very unlikely to leave (reverse coded)	BRlea2
		55. If AI is introduced, I… continue working here 1 - prefer very much to 2 – prefer to 3 - neutral 4 - prefer not to 5 - prefer very much not to	BRlea3
		If AI is introduced, it is… for me to spend my career in this organization 1 - very important 2 - fairly important 3 - neutral 4 – not important 5 - not important at all	BRlea4

1.5 Perceived organisational support

Construct	***Measurement item***	***Variable name***
Perceived organisational support (Eisenberger, Huntington, Hutchison and Sowa, 1986)	My organisation strongly considers my personal values and goals in decision making	POS1
	My organisation cares about the voice of employees	POS2
	My organisation genuinely cares about each individual's well-being	POS3
	I can get immediate assistance from my co-workers if I need it	POS4
	Any honest mistakes will be forgiven	POS5
	My organisation is willing to help me if I need a special favor	POS6
	If given the opportunity, my organisation would take full advantage of me (reverse-coded)	POS7
	My organisation shows very little consideration for me (reverse-coded)	POS8

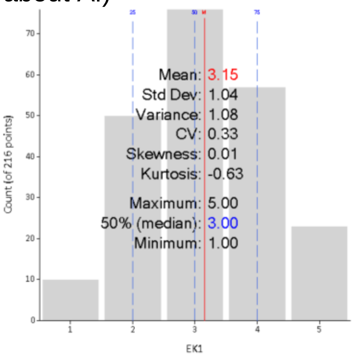
1.6 Commitment to organisation

Construct	***Measurement item***	***Variable name***
Affective commitment to the organisation (Meyer et al., 1993)	I would be very happy to spend the rest of my career with this organisation	COaff1
	I really feel as if this organisation problems are my own	COaff2
	I do not feel a strong sense of “belonging” to my organisation (reverse-coded)	COaff3
	I do not feel “emotionally attached” to this organisation (reverse-coded)	COaff4
	I do not feel like “part of the family” at my organisation (reverse-coded)	COaff5
	This organisation has a great deal of personal meaning to me	COaff6
Continuance commitment to the organisation (Meyer et al., 1993)	Right now, staying with my organisation is a matter of necessity as much as desire	COcnt1
	It would be very hard for me to leave my organisation right now, even if I wanted to	COcnt2
	Too much of my life would be disrupted if I decided I wanted to leave my organisation now	COcnt3
	I feel that I have too few options to consider leaving this organisation	COcnt4
	If I have not already put so much of myself into this organisation, I might consider working elsewhere	COcnt5
	One of the few negative consequences of leaving this organisation would be scarcity of available alternatives	COcnt6
Normative commitment to the organisation (Meyer et al., 1993)	I do not feel any obligation to remain with my current employer (reverse-coded)	COnrm1
	Even if it were to my advantage, I do not feel it would be right to leave my organisation now	COnrm2
	I would feel guilty if I left my organisation now	COnrm3
	This organisation deserves my loyalty	COnrm4
	I would not leave my organisation right now because I have a sense of obligation to the people in it	COnrm5
	I owe a great deal to my organisation	COnrm6

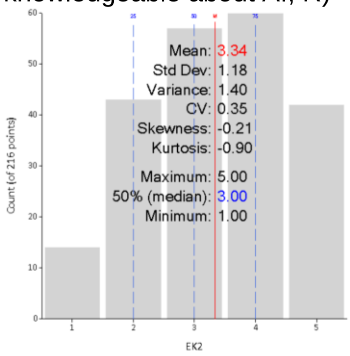
Appendix 2. Histograms of the measurement items variables

2.1 Employee subjective knowledge of AI (EK)

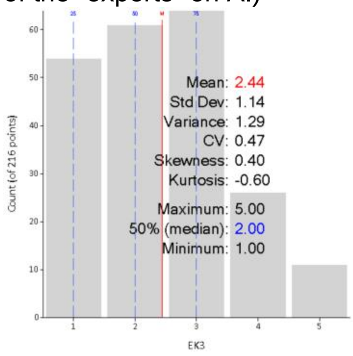
EK1 (I know pretty much about AI)



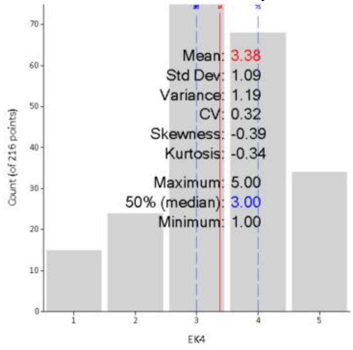
EK2 (I do not feel very knowledgeable about AI, R)



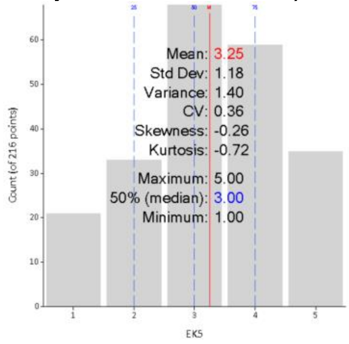
EK3 (Among friends, I'm one of the "experts" on AI)



EK4 (Compared to most, I know less about AI, R)

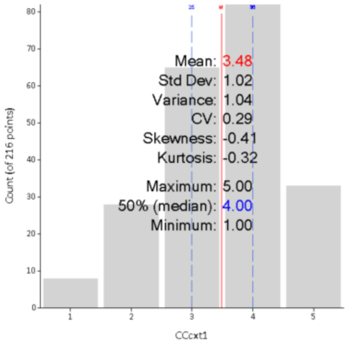


EK5 (When it comes to AI, I really don't know a lot, R)

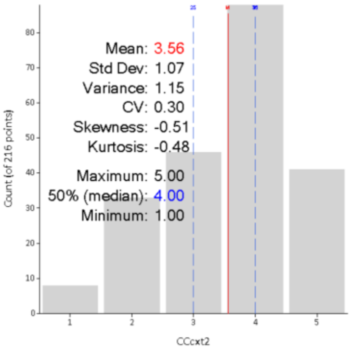


2.2 Perceived cognitive capabilities of AI (CC)

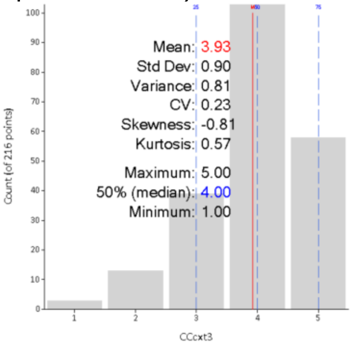
CCcxt1 (contextual ambiguity)



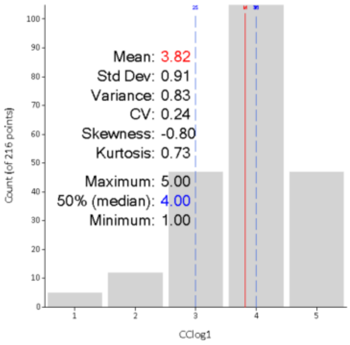
CCcxt2 (specific jargons and slangs)



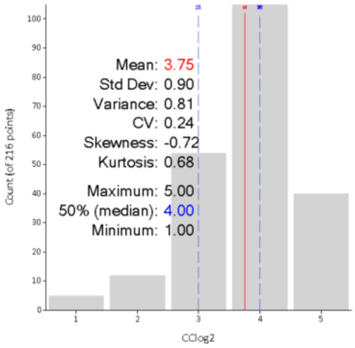
CCcxt3 (learn new knowledge to understand a specific context)



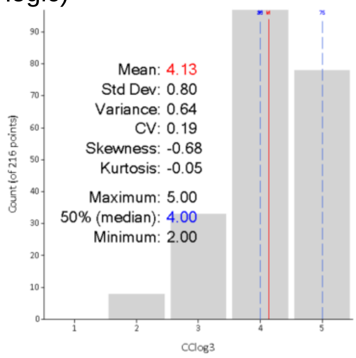
CClog1 (clear logic)



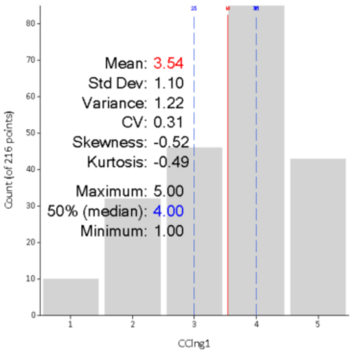
CClog2 (comprehensive logic)



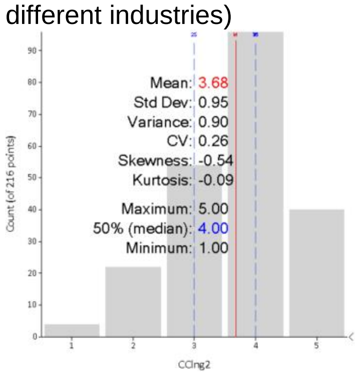
CClog3 (possible to improve and adjust the AI system's logic)



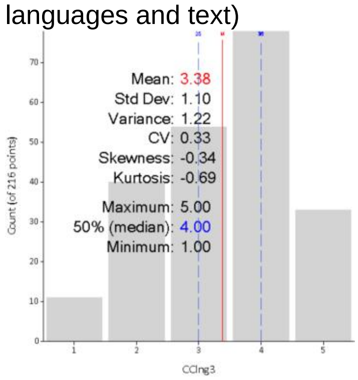
CClng1 (process languages and texts like a human)



CClng2 (understand jargons and terminologies from different industries)

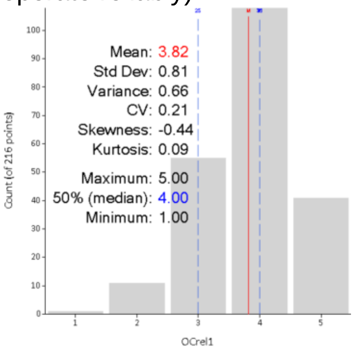


CClng3 (understand the underlying meaning through languages and text)

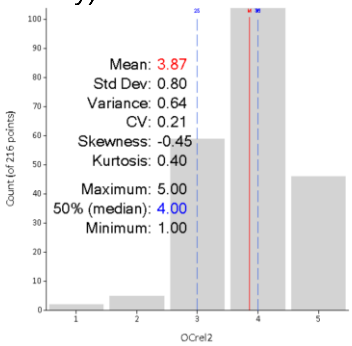


2.3 Perceived operational capabilities of AI (OC)

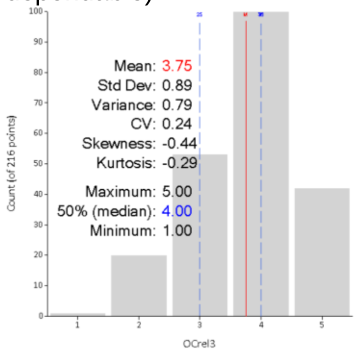
OCrel1 (AI system would operate reliably)



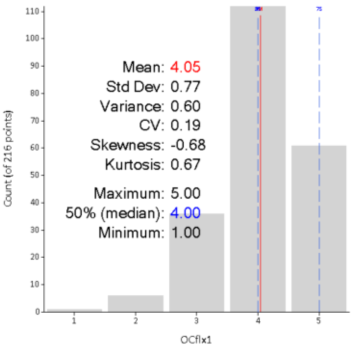
OCrel2 (would perform reliably)



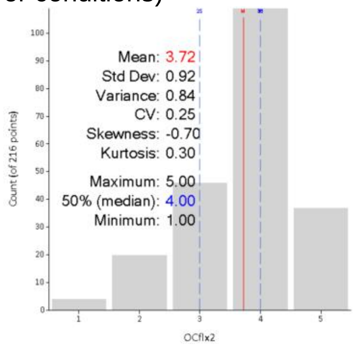
OCrel3 (AI system would be dependable)



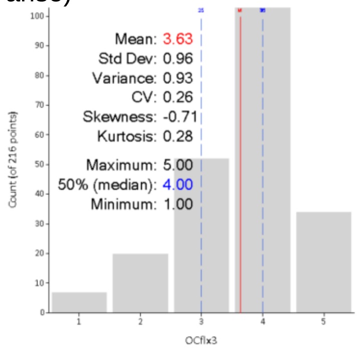
OCflx1 (AI system adaptable for a variety of needs)



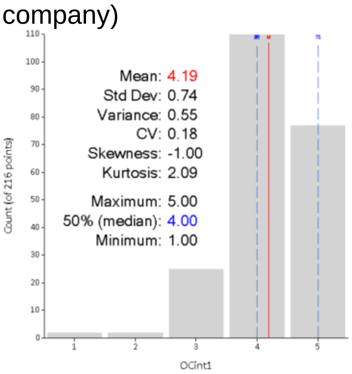
OCflx2 (AI system flexibly adjustable to new demands or conditions)



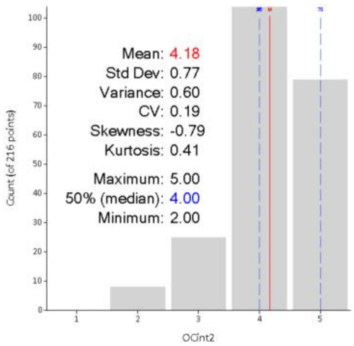
OCflx3 (versatile in addressing needs as they arise)



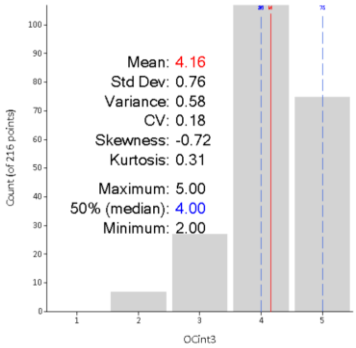
OCint1 (AI system could effectively integrate data from different areas of the company)



OCint2 (could pull together information from different places in the company)

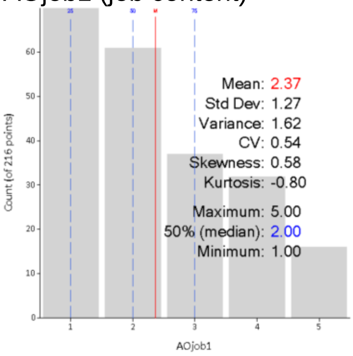


OCint3 (effectively combine data from different areas of the company)

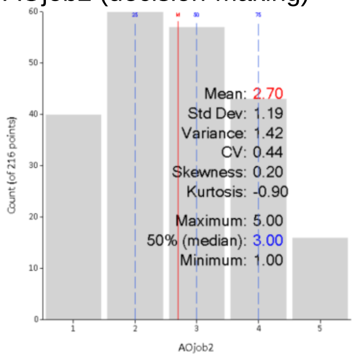


2.4 Anticipated adverse outcomes (AO)

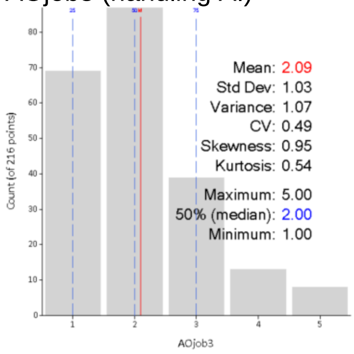
AOjob1 (job content)



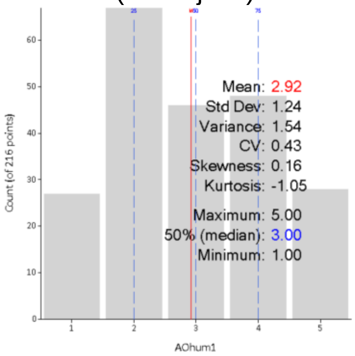
AOjob2 (decision-making)



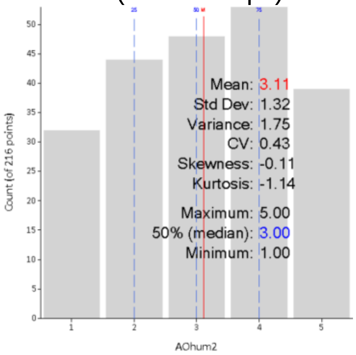
AOjob3 (handling AI)



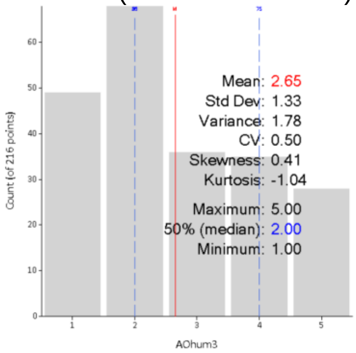
AOhum1 (fewer jobs)



AOhum2 (relationships)

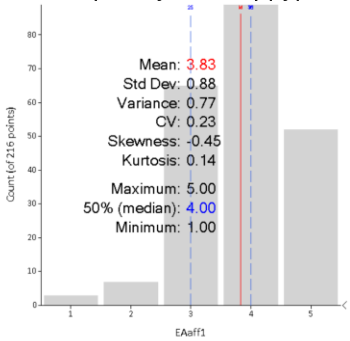


AOhum3 (human usefulness)

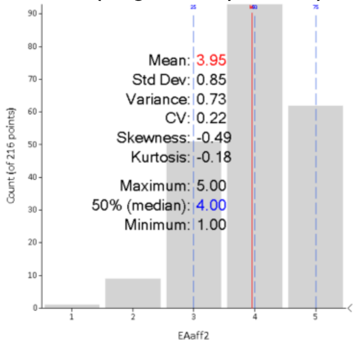


2.5 Employee attitudes to AI (EA)

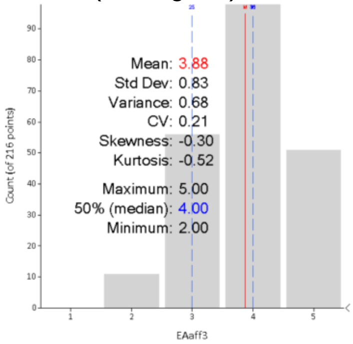
EAaff1 (annoyed - happy)



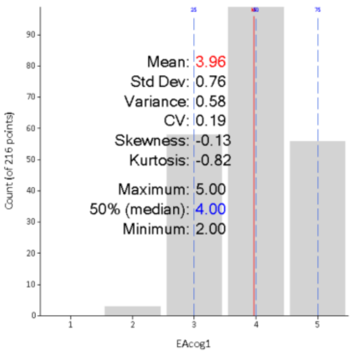
EAaff2 (negative - positive)



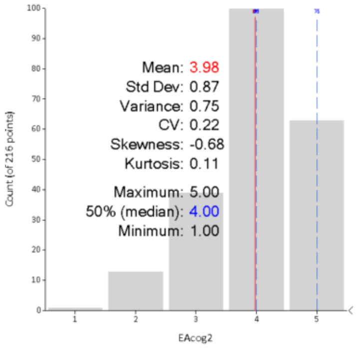
EAaff3 (bad - good)



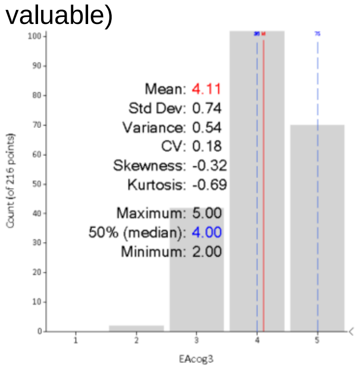
EAcog1 (foolish - wise)



EAcog2 (harmful - beneficial)

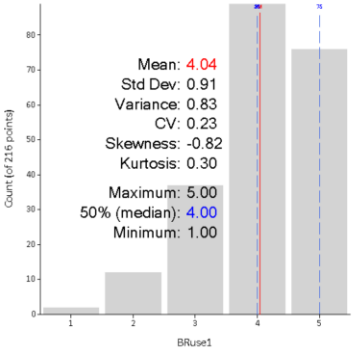


EAcog3 (worthless - valuable)

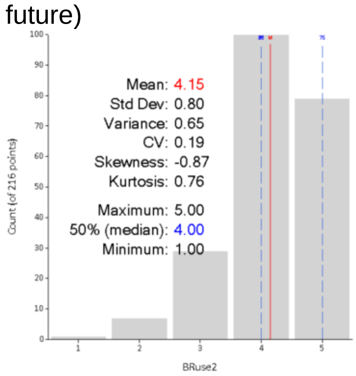


2.6 Behavioral responses: Intention to use AI (BRuse)

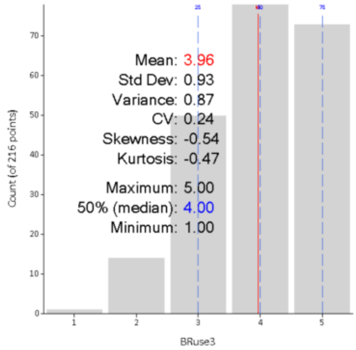
BRuse1 (I intend to use the AI system in the future)



BRuse2 (I expect that I would use the AI system in the future)

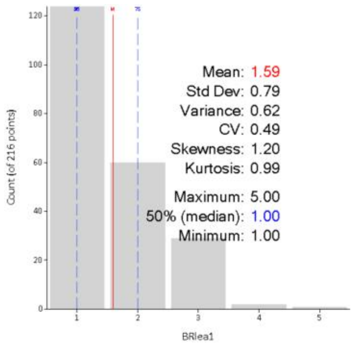


BRuse3 (I plan to use the AI system in the future)

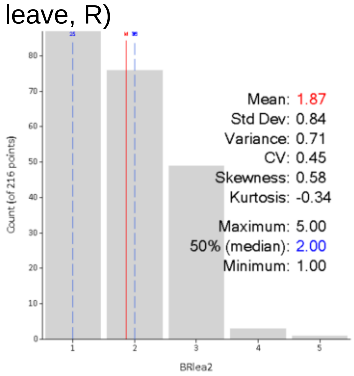


2.7 Behavioral responses: Intention to leave the company if AI is implemented (BRlea)

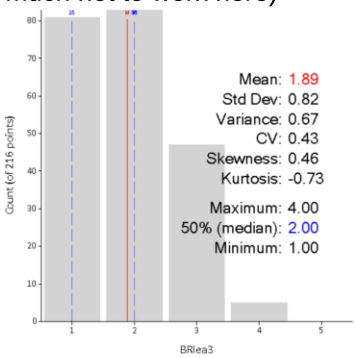
BRlea1 (1 - definitely not leave, 5 – definitely leave)



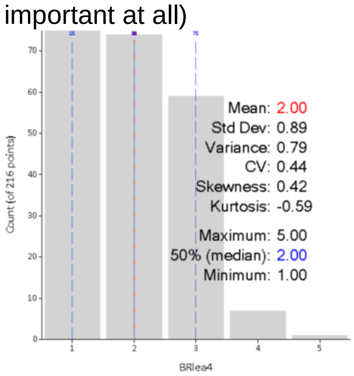
BRlea2 (1 - immediately plan to leave, 5 - very unlikely to leave, R)



BRlea3 (1 - prefer very much to work here, 5 – prefer very much not to work here)

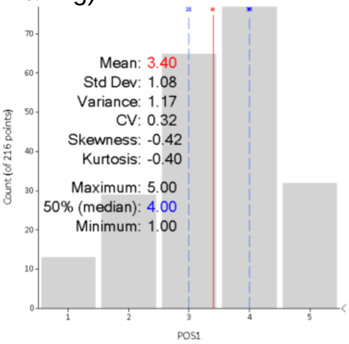


BRlea4 (1 - very important to spend career here, 5 – not important at all)

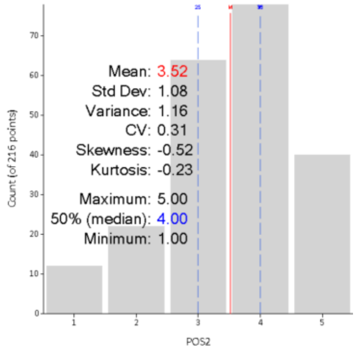


2.8 Perceived organisational support (POS)

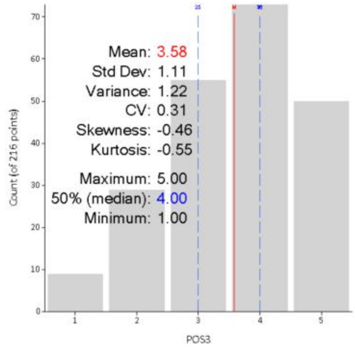
POS1 (organisation strongly considers personal values and goals in decision making)



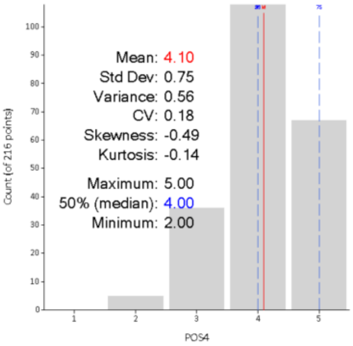
POS2 (organisation cares about the voice of employees)



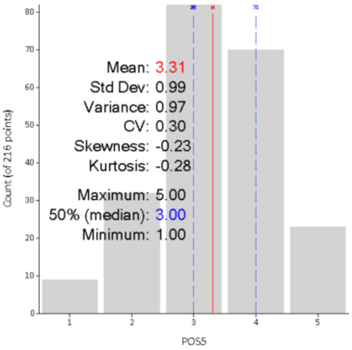
POS3 (organisation genuinely cares about each individual's well-being)



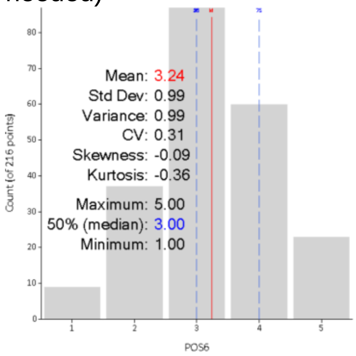
POS4 (assistance from co-workers)



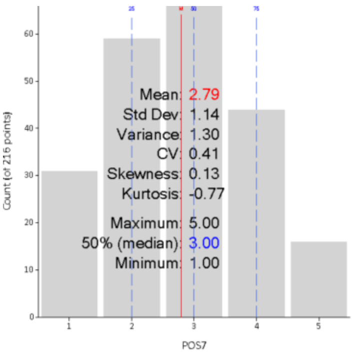
POS5 (honest mistakes forgiven)



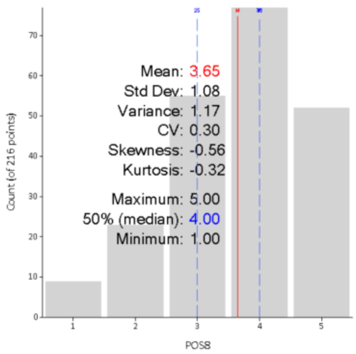
POS6 (organisation willing to help if a special favor is needed)



POS7 (if given an opportunity, organisation would take full advantage of me)

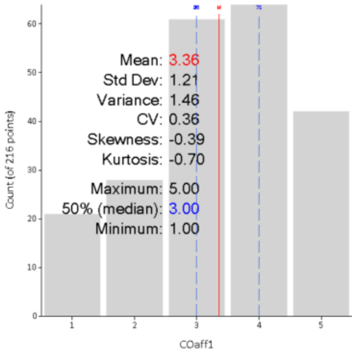


POS8 (organisation shows very little consideration for me)

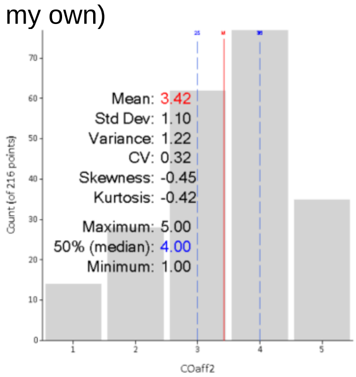


2.9 Commitment to organisation: Affective (COaff)

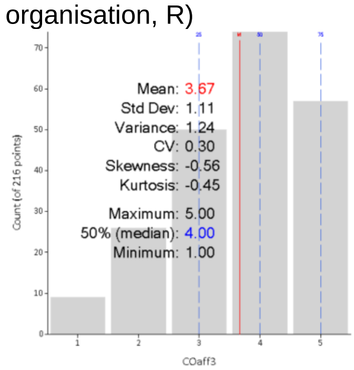
COaff1 (happy to spend the rest of my career here)



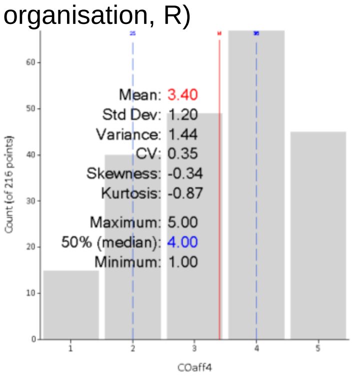
COaff2 (I really feel as if this organisation problems are my own)



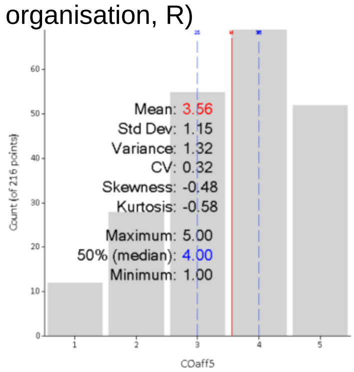
COaff3 (I do not feel a strong sense of “belonging” to my organisation, R)



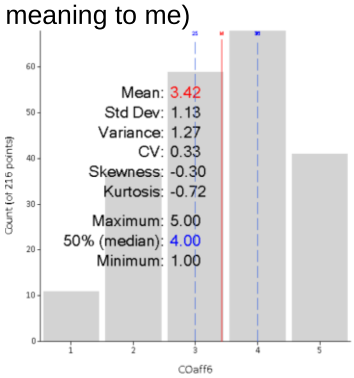
COaff4 (I do not feel “emotionally attached” to this organisation, R)



COaff5 (I do not feel like “part of the family” at my organisation, R)

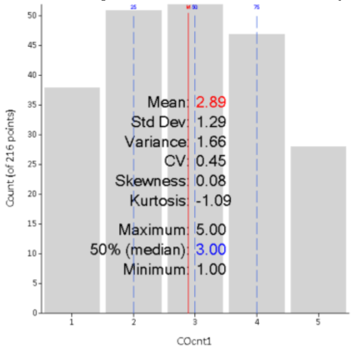


COaff6 (This organisation has a great deal of personal meaning to me)

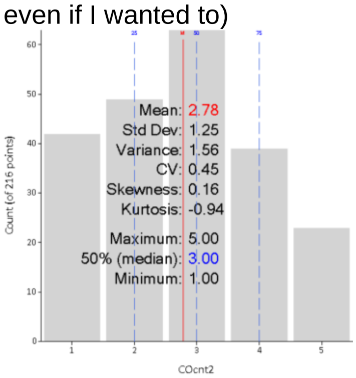


2.10 Commitment to organisation: Continuance (COcnt)

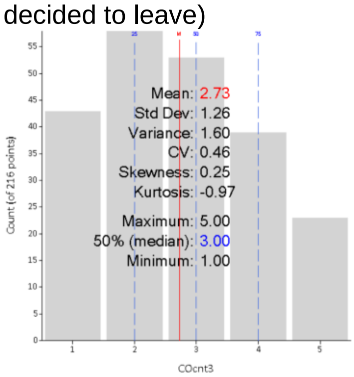
COcnt1 (staying with my organisation is a matter of necessity as much as desire)



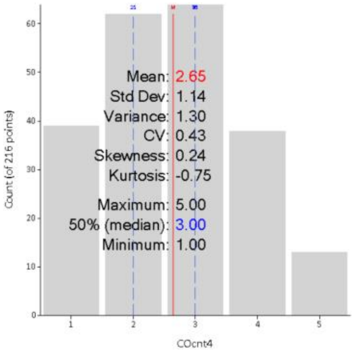
COcnt2 (hard for me to leave my organisation right now, even if I wanted to)



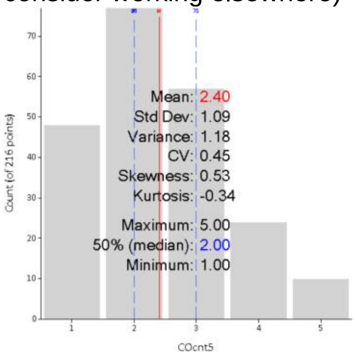
COcnt3 (Too much of my life would be disrupted if I decided to leave)



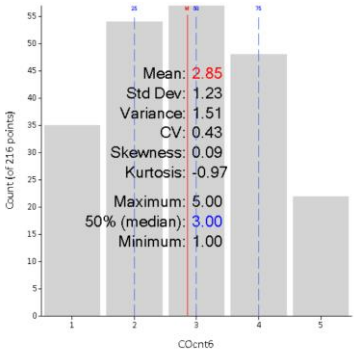
COcnt4 (I have too few options to consider leaving this organisation)



COcnt5 (If I have not already put so much of myself into this organisation, I might consider working elsewhere)

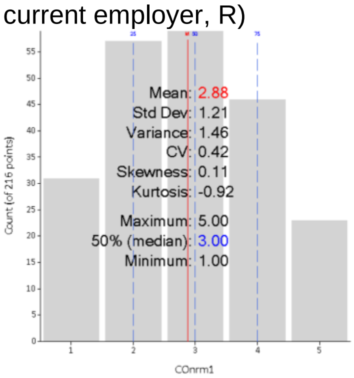


COcnt6 (scarcity of available alternatives)

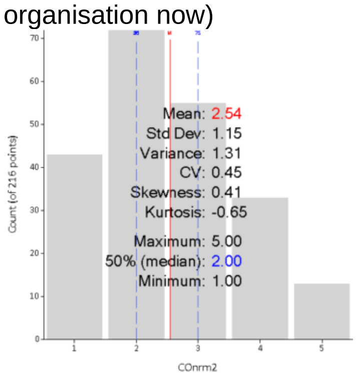


2.11 Commitment to organisation: Normative (COnrm)

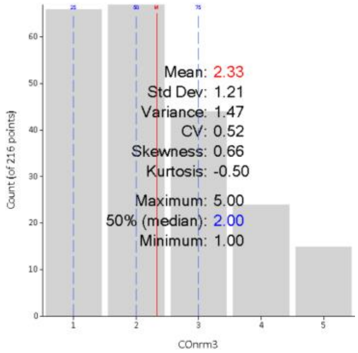
COnrm1 (I do not feel any obligation to remain with my current employer, R)



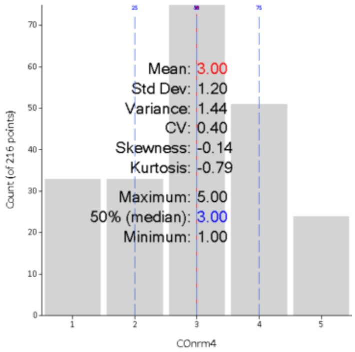
COnrm2 (I do not feel it would be right to leave my organisation now)



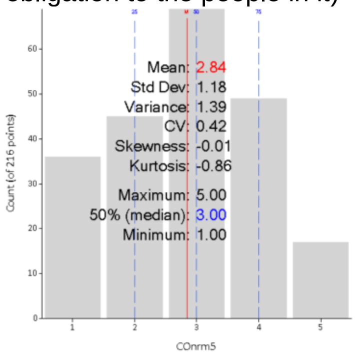
COnrm3 (I would feel guilty if I left my organisation now)



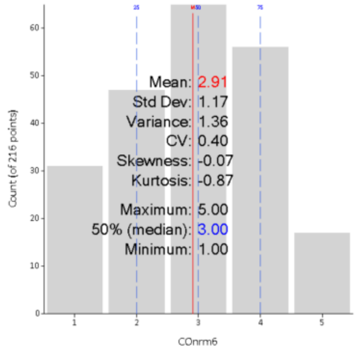
COnrm4 (This organisation deserves my loyalty)



COnrm5 (I would not leave my organisation right now because I have a sense of obligation to the people in it)



COnrm6 (I owe a great deal to my organisation)



Appendix 3. Factor analysis – KMO and Barlett's test

KMO and Barlett's test	*Variable name*	*KMO and Barlett's test*	*Sig*	*Ranking*
Employee knowledge	EK1 EK2 EK3 EK4 EK5	0.797	<0.001	Middling
Context understanding	CCctx1 CCctx2 CCctx3	0.664	<0.001	Mediocre
Logic transparency	CClog1 CClog2 CClog3	0.658	<0.001	Mediocre
Language understanding	CClng1 CClng2 CClng3	0.720	<0.001	Middling
Reliability	OCrel1 OCrel2 OCrel3	0.679	<0.001	Mediocre
Flexibility	OCflx1 OCflx2 OCflx3	0.657	<0.001	Mediocre
Integrability	OCint1 OCint2 OCint3	0.738	<0.001	Middling
Job-related	AOjob1 AOjob2 AOjob3	0.652	<0.001	Mediocre
Humanity-related	AOhum1 AOhum2 AOhum3	0.723	<0.001	Middling
Employee affective attitude towards AI	EAaff1 EAaff2 EAaff3	0.773	<0.001	Middling
Employee cognitive attitude towards AI	EAcog1 EAcog2 EAcog3	0.761	<0.001	Middling
Intention to use company AI	BRuse1 BRuse2 BRuse3	0.757	<0.001	Middling
Intention to leave the company	BRlea1 BRlea2 BRlea3 BRlea4	0.753	<0.001	Middling
Perceived organisational support	POS1 POS2 POS3 POS4 POS5 POS6 POS7	0.814	<0.001	Meritorious
Affective	COaff1 COaff2 COaff3 COaff4 COaff5 COaff6	0.832	<0.001	Meritorious
Continuance	COcnt1 COcnt2 COcnt3 COcnt4 **COcnt5** COcnt6	0.731	<0.001	Middling
Normative	COnrm1 COnrm2 COnrm3 COnrm4 COnrm5 COnrm6	0.838	<0.001	Meritorious

Appendix 4. Factor analysis – Total variance explained

Dimension	Variable name	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
		Total	*% of Variance*	*Cumulative %*	*Total*	*% of Variance*	*Cumulative %*	*Total*	*% of Variance*	*Cumulative %*
Employee knowledge	EK1	2.955	59.097	59.097	2.955	59.097	59.097			
	EK2	0.721	14.422	73.519						
	EK3	0.602	12.038	85.557						
	EK4	0.379	7.580	93.137						
	EK5	0.343	6.863	100.000						
Context understanding	CCctx1	1.886	62.863	62.863	1.886	62.863	62.863			
	CCctx2	0.625	20.827	83.689						
	CCctx3	0.489	16.311	100.000						
Logic transparency	CClog1	1.955	65.173	65.173	1.955	65.173	65.173			
	CClog2	0.634	21.131	86.304						
	CClog3	0.411	13.696	100.000						
Language understanding	CClng1	2.239	74.635	74.635	2.239	74.635	74.635			
	CClng2	0.417	13.893	88.528						
	CClng3	0.344	11.472	100.000						
Reliability	OCrel1	2.161	72.046	72.046	2.161	72.046	72.046			
	OCrel2	0.523	17.438	89.484						
	OCrel3	0.315	10.516	100.000						
Flexibility	OCflx1	2.241	74.711	74.711	2.241	74.711	74.711			
	OCflx2	0.534	17.807	92.518						
	OCflx3	0.224	7.482	100.000						
Integrability	OCint1	2.562	85.416	85.416	2.562	85.416	85.416			
	OCint2	0.280	9.335	94.751						
	OCint3	0.157	5.249	100.000						
Job-related	AOjob1	2.088	69.592	69.592	2.088	69.592	69.592			
	AOjob2	0.599	19.973	89.564						
	AOjob3	0.313	10.436	100.000						
Humanity-related	AOhum1	2.324	77.457	77.457	2.324	77.457	77.457			
	AOhum2	0.399	13.292	90.750						
	AOhum3	0.278	9.250	100.000						
Employee affective attitude towards AI	EAaff1	2.728	90.937	90.937	2.728	90.937	90.937			
	EAaff2	0.156	5.211	96.148						
	EAaff3	0.116	3.852	100.000						
Employee cognitive attitude towards AI	EAcog1	2.571	85.689	85.689	2.571	85.689	85.689			
	EAcog2	0.222	7.401	93.089						
	EAcog3	0.207	6.911	100.000						
Intention to use company AI	BRuse1	2.638	87.946	87.946	2.638	87.946	87.946			
	BRuse2	0.223	7.426	95.372						
	BRuse3	0.139	4.628	100.000						
Intention to leave the company	BRlea1	2.528	63.207	63.207	2.528	63.207	63.207			
	BRlea2	0.689	17.217	80.424						
	BRlea3	0.463	11.575	91.999						
	BRlea4	0.320	8.001	100.000						
Perceived organisational support	POS1	3.519	50.270	50.270	3.519	50.270	50.270	3.518	50.260	50.260
	POS2	1.006	14.374	64.643	1.006	14.374	64.643	1.007	14.383	64.643
	POS3	0.845	12.074	76.717						
	POS4	0.661	9.446	86.163						
	POS5	0.483	6.893	93.056						
	POS6	0.336	4.802	97.858						
	POS7	0.150	2.142	100.000						
	POS8									
Affective	COaff1	3.455	57.581	57.581	3.455	57.581	57.581			
	COaff2	0.908	15.130	72.711						
	COaff3	0.537	8.945	81.656						
	COaff4	0.471	7.858	89.513						
	COaff5	0.341	5.677	95.190						
	COaff6	0.289	4.810	100.000						
Continuance	COcnt1	2.590	43.164	43.164	2.590	43.164	43.164	1.969	32.815	32.815
	COcnt2	1.063	17.720	60.883	1.063	17.720	60.883	1.684	28.068	60.883
	COcnt3	0.811	13.521	74.404						
	COcnt4	0.675	11.254	85.658						
	COcnt5	0.461	7.685	93.343						
	COcnt6	0.399	6.657	100.000						
Normative	COnrm1	3.408	56.807	56.807	3.408	56.807	56.807			
	COnrm2	0.860	14.325	71.132						
	COnrm3	0.560	9.330	80.462						
	COnrm4	0.522	8.696	89.158						
	COnrm5	0.334	5.563	94.721						
	COnrm6	0.317	5.279	100.000						

Appendix 5. Ethical clearance

Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Approved

Dear Yelena van der Grijp,

Please be advised that your application for Ethical Clearance has been approved.
You are therefore allowed to continue collecting your data.
We wish you everything of the best for the rest of the project.

Ethical Clearance Form

Kind Regards

This email has been sent from an unmonitored email account. If you have any comments or concerns, please contact the GIBS Research Admin team.

Masters Research

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