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HUMAN-AI COLLABORATION IN ORGANISATIONS: A LITERATURE REVIEW ON ENABLING VALUE CREATION

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Research Paper

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Abstract

The augmentation of human capability with artificial intelligence is integral to the advancement of next generation human-machine collaboration technologies designed to drive performance improvement and innovation. Yet we have limited understanding of how organisations can translate this potential into creating sustainable business value. We conduct an in-depth literature review of interdisciplinary research on the challenges and opportunities in organisational adoption of human-AI collaboration for value creation. We identify five research positions central to how organisations can integrate and align the socio-technical challenges of augmented collaboration, namely strategic positioning, human engagement, organisational evolution, technology development and intelligence building. We synthesise the findings into an integrated model that focuses organisations on building the requisite internal microfoundations for the systematic management of augmented systems.

Keywords: Augmented intelligence; Human – machine collaboration; Human-AI value creation

1 Introduction

The rise of artificial intelligence (AI) is driving what many researchers and industry commentators are calling the 'fourth industrial revolution' and is steadily disrupting traditional business models and practices of strategy, innovation and performance management (Longo et al., 2020; Sharma & Rana, 2020; Sima et al., 2020). This is particularly true of the new generation of AI-enabled technologies which has evolved over the last 10 years, largely driven by significant advancement of technological capabilities of data extraction, storage and analysis, machine learning, computing power, and algorithmic capability (Collins et al., 2021; Duan et al., 2019; Dwivedi et al., 2021; Berente et al., 2021).

Despite the astonishing rate of progress with AI technology, the complex challenges in the current business environment cannot be solved by machines alone and require robust human-machine hybrid solutions to realize the full potential of both AI and human capability (Akata et al., 2020; de Cremer et al., 2021; Dellermann, Lipusch, et al., 2019; Demartini et al., 2016; Parasuraman & Wickens, 2008). However, one of the key challenges for organisations and technology developers is to design systems and AI-enabled technologies that adequately address the augmentation design problem, which we define as the arrangement and balance of psychological, social, organisational, information and technical systems to produce an optimal dynamic, productive, ethical and creative interplay between humans and intelligent machines. All design problems are largely undetermined, are often complicated by paradoxical situations and are situated within the challenges of their specific contexts (Dorst, 2004; 2006). This lies at the heart of the issues that we have identified in our review on augmented intelligence.

In our study we performed an interdisciplinary review of literature focused on the organisational challenges and enablers of realising value from augmenting artificial intelligence with human and organisational capability. To this end, we adopted an organization-level perspective and developed the core research question of: *What are the key enablers of organisational value creation for augmented intelligence?* Our analysis shows that the domain is challenged by mixed and inconclusive results on the value creation of AI applications and highlights a complex array of advancements that are required in human-machine interaction, dynamic work design, algorithmic behaviour, machine learning models, and organisation systems adaption.

We have taken a broad interpretation of value creation, as what is perceived as value creation depends on the strategic goals of an organization (Günther et al., 2017; Ghoshal et al., 2014) and is derived from multi-dimensional value-creating practices (Suseno et al., 2018; Sanchez-Fernandez & Iniesta-Bonillo, 2007). We were also cognizant of what is still perceived as a causal relationship between IS investments and business value as it remains partly unexplained, mainly driven by limitations imposed by the ambiguity and fuzziness of IS business value and the unexplained process of creating internal and competitive value (Coombs et al., 2020; Schryen 2013). Empirical research on the value of AI is still in rudimentary state and there is a lack of consensus on concerning the mechanisms that can generate business value (Duan et al., 2019; Mikalef et al., 2021). With this in mind, our position in reviewing the literature was to note the different ways of how value creation was treated in the context of human-machine collaboration at the organisational level and identify the common denominators in our analysis.

Our research contribution is threefold. First, we identify five research positions central to how organisations can improve value-creation opportunities from artificial intelligence (AI) that are framed around strategic positioning, human engagement, organisational evolution and technology development. Second, we call for empirical studies that build on these positions in further research that are unique to augmentation design problem identified in our thematic analysis. Third, we identify an ecosystem approach to systems development and in building organisational microfoundations that has implications for practice in terms of how organizations may realise value from augmented intelligence.

2 Methodology

The methodology for this paper was based on a literature review and a thematic analysis of the key findings to address our research question. Our literature review consisted of two key steps: First we commenced with an exploratory search for systematic literature reviews (SLR) published in high quality peer-reviewed journals, and this search was then extended to other scoping studies and reviews in information systems (IS) literature. This first step was a narrative or traditional literature review (Byrne, 2016; Paré et al., 2015; Green et al., 2006) and we took this approach due to the lack of definitional clarity and consistency of use of the terms ‘artificial intelligence’ and ‘augmented intelligence’ and the nascent and fragmented state of research in our specific research domain. This allowed us to scope out and add clarity to our topic before commencing to a wider and more in-depth literature search. The second step consisted of a systematic literature review guided by Okoli (2015) and Kitchenham et.al (2009; 2011) which consisted of testing several search queries on the SCOPUS database and this method identified the bulk of the literature that we reviewed for this study. The key components of our methodology are detailed as follows:

2.1 Definitions

Despite the plethora of research in the field, there is still no common set of clear definitions or understanding of artificial intelligence, augmented intelligence or value creation which is an indication of the diversity of the functional intent, technological forms and disciplinary origins of each of these domains. The following definitions have been used to guide this review:

Artificial intelligence: We define AI as intelligent technologies that simulate and extend human intelligence in information systems and business applications which includes: machine learning, computer vision, natural language programming, robotics, speech recognition, decision support systems, expert systems, automation and algorithmic management.

Augmented intelligence: We define augmented intelligence as a process or application that combines the unique capabilities of both humans and AI technologies to enhance decision-making outcomes of organizational systems. In augmented systems AI technologies extend human skills and capability (Jarrahi 2018) and alter work systems to enable strategic human-AI partnerships (Davenport 2018).

Value creation: Value creation is defined as the impact of augmented intelligence systems on organisational performance and capability that is aligned with their strategic goals. From the literature in our sample value creation includes a broad range of organisational goals such as efficiency in decision making, teamwork in information and knowledge exchange, increased productivity, cost reduction and improved customer experiences.

2.2 The search process

The search process in this review was a combination of both string-based search as well as backward and forward searches. We commenced our review with an exploratory search for systematic literature reviews (SLR) in high quality peer-reviewed journals in the key domains relevant to our research objective which included AI and augmentation in information systems, management research, and organisation or systems research. This initial review was conducted with a search on the SCOPUS database which identified seven key relevant reviews that had systematically reviewed 438 research papers between them. These SLAs focussed on artificial intelligence in information systems research (Borges et al., 2021; Collins et al., 2021; Rzepka & Berger, 2018) as well as from organisation and management research (Cubric, 2020; Enholm et al., 2021; Langer & Landers, 2021; Niehaus & Wiesche, 2021). This search was then extended to other scoping studies and reviews in IS literature which were added to our review (Coombs et al., 2020; Dwivedi et al., 2021; Marabelli et al., 2021; Wagner, 2017).

The next phase of the literature review was extended beyond SLAs and a systematic search was conducted on the SCOPUS database and several search queries were tested to find the right balance of articles that could directly address our core research question. As noted above, we faced several challenges associated with definitional issues of the key terms and the overwhelming technology or software engineering focus of the results. The majority of these search results were pilot studies or experiments of narrow AI applications in a specific field, or in application areas were not generalizable across our research question. The string needed restructuring several times to find the relevant core of the corpus. The final search string that was used is as follows:

TITLE-ABS-KEY ((((ai OR "artificial intelligence" OR "machine learning" OR "neural networks" OR "intelligent agent" OR "deep learning") AND (tam OR utaut OR "technology acceptance" OR adoption OR intention OR attitude) AND (augmentation OR augment OR co nvergence OR "human machine interaction" OR "human robot interaction" OR "algorithmic co-workers" OR "algorithmic colleagues" OR "algorithmic management"))))

The process identified 961 papers, of which 254 qualified for the inclusion criteria. The inclusion criteria included a limitation of studies published in journals, published between 2010 to 2022, and specifically in business domains. These included the SCOPUS search categories of business, economics, decision-making, psychology, arts and neuroscience. It should be noted that domains that were excluded from our review included medicine and nursing; despite the high level of research that has been undertaken in human-machine augmentation in these domains our preliminary research concluded that results in this domain were highly specialised and were not transferable or generalizable to business domains (Cubric, 2020; Langer & Landers, 2021) and may not be able to provide insight to our research focus.

Next we conducted a review of titles and abstracts to identify the most relevant papers for our review which reduced the total number of papers to 110. These papers were then read in full and the total number of papers selected for inclusion was reduced to 44 due to the high number of papers focussed on engineering or highly experimental or small scale pilots or experiments, or those without a specific focus on augmented intelligence in business applications. We then conducted a series of forward and backward searches and identified a further 114 papers for inclusion. The backward and forward searches were used to expand outside from the core of the corpus which allowed us to explore a greater level of depth in the material, and resulted in a significant part of the literature reviewed in our paper. A total of 158 papers were included in the review and an in-depth analysis was undertaken to identify key findings, themes and research directions. An outline of the search process is summarised in Figure 1 below.

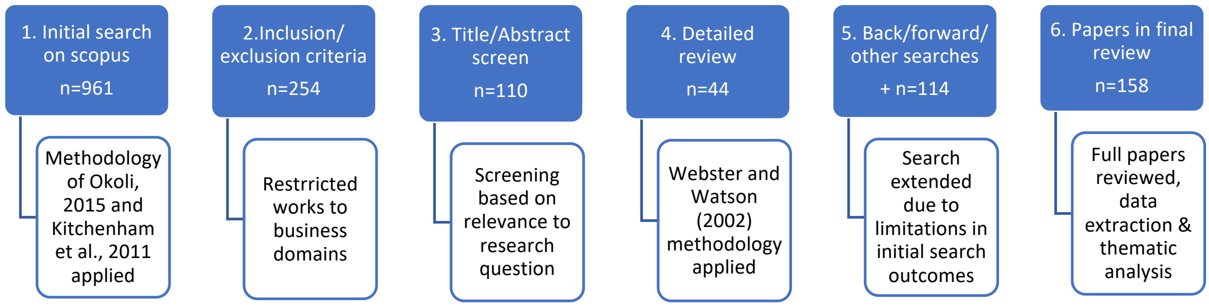

Figure 1. The literature search process.

2.3 Data extraction and thematic analysis

In the data extraction phase the methodologies of Okoli (2015) and Kitchenham et.al (2009; 2011) were used to systematically extract the relevant data from each study and synthesize the findings. The metadata of all the papers were added to an Excel spreadsheet and further fields were created to list the findings or themes, codes and analysis. All papers were then carefully read and annotated, and key themes were identified using inductive content analysis (Kolbe & Burnett 1991). In our data extraction 75 themes emerged from the articles inductively by systematically interpreting the nature, meaning and relevance of the content to our specific research focus (Vaismoradi et al., 2016; Braun & Clarke, 2006; Jones, Coviello & Tang, 2011). We took a socio-technical systems (STS) approach to our research and acknowledge that we therefore influenced by the core tenets of STS architecture of leadership, people, technology, structures, environment, and goals and tasks (Appelbaum, 1997) in how we coded and analyzed the literature.

The key steps we undertook in our analysis was as follows:

(a) We commenced our analysis focusing at the organization level by drawing out the key themes in the selected literature pertaining to our research question in the form of and integrative process 'free coding' and reached a saturation point at 75 themes which are detailed in Appendix 1.

(b) After several iterations we distilled the 75 themes into descriptive groupings and attained conceptual saturation at ten categories listed in Table 1. Our initial list began with 22 separate categories but through successive iterations we synthesized these into 10 overarching categories. This was particularly relevant to categories related to the topics of technology and human-machine interaction given the wide diversity of themes and issues identified in the literature. Our objective with the iterative distillation of the themes into categories was in line with the learnings from Williams & Moser (2019) that each iteration assists in the cumulative construction of meaning from the data and locate the genesis of the phenomenon under our review.

(c) We further distilled the ten categories into four overarching thematic clusters coded as human engagement, organisational evolution, strategic positioning and technology development. In the early stages of our analysis we identified six core categories that aligned to the work of Appelbaum (1997) however we found that for a more concise reflection of the findings in our sample literature it made more sense to combine Appelbaum's (1997) 'structures' and 'goals/tasks' into our cluster of *organisational evolution* and combined 'leadership' and 'environment' into *strategic positioning*. We argue that our 10 core categories and four thematic clusters locate the genesis of the phenomena of our topic and highlights the story in our data of the critical role and interdependency of business strategy, human engagement, systems adaption and technology development that form a four-point approach that organisations use to extract value from augmented intelligence. A summary of our thematic analysis is provided in Table 1 below, with a full description provided in Appendix 1.

4 Thematic Clusters	10 Key Categories	75 Themes
Strategic Positioning	Extant Performance	10
	Value Creation Capability	8
	Governance and Ethics	4
Human Engagement	Engagement and Motivation	9
	Human-Machine Interaction	9
Organisational Evolution	Systems Enablement	13
	Reconstructing Work Design	3
Technology Development	AI Acceptance Complexities	6
	Algorithmic Behavior	7
	Next Gen Technology	6

Table 1 Outline of Thematic Analysis: Categories and Clusters

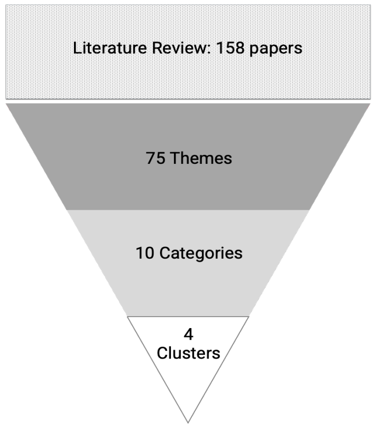

Figure 2 Distillation of the data

The final stage of our analysis was a quality check and sensemaking of the thematic analysis and this was done by exporting the data from Excel into the visual interactive mind-mapping tool Miro. This allowed us to visually display, reorganize and iterate the groupings of the themes into analytical categories and clusters. The final set of data was written in a tree structure and provided in Appendix 1.

3 Key findings

In this section we present a discussion on our key findings to our question: *What are the key enablers of value creation for augmented intelligence?* We address our findings by each of the four thematic clusters and provide a definition of each cluster at the beginning of each section. We also offer a research position on each cluster pertaining to implications for practice and on future research directions as indicators of the requisite microfoundations needed to build value-creation capability.

3.1 Strategic positioning

Strategic positioning is defined as the ability of organisations to manage the complexities of deriving value from AI, achieving clarity in the source of truth from research, and smart strategic decision-making on AI investment and implementation. There are three categories within this cluster that enable strategic positioning: extant performance, value-creation capability, and governance and ethics.

The category of ***extant performance*** is defined as access to critical knowledge of the performance of AI technologies. Several papers in our sample found that there was limited empirical evidence to support expositions of the decision-making effectiveness and performance outcomes of AI automation and augmentation, and at best it was found to have shown mixed results (Borges et al., 2021; Collins et al., 2021; Rzepka & Berger, 2018; Enholm et al., 2021; Langer & Landers, 2021; Niehaus & Wiesche, 2021; Cubric 2020). Furthermore, limited by a lack of generalisability of results across application domains, particularly in how learnings may be applied to business domains (Cubric, 2020; Langer & Landers, 2021; Morley et al., 2021; Rzepka & Berger, 2018). Successes in terms of value creation were concentrated in use-cases in process automation, particularly in manufacturing which are comparatively the least expensive and easiest to implement AI systems (Enholm et al., 2021; Leyer & Schneider, 2021; Parasuraman & Wickens, 2008; Shea et al., 2019) and in the medical field (Aguiar et al., 2013; Aydin et al., 1994; Loh, 2018; Maadi et al., 2021).

The general consensus in our sample is that organisations are struggling to realise value from AI investments and are often reporting their performance results in an overly optimistic way and frequently do not include an evaluation of the results in practice (Cubric, 2020; Enholm et al., 2021; Newlands, 2021). These reporting anomalies make it difficult to explain the variable or contradictory results that have been identified and limits the generation of insight into how AI performance can be improved (Leone et al., 2021; Coombs et al., 2020; Langer & Landers 2021).

The category of ***value creation capability*** contained themes related to the need of organisations to build the internal skills and capability to extract value from AI technology. Several papers identified that organisations are constrained by the limited nature and availability of rigorous research on AI value creation that can objectively inform decision-making on AI investment and organisational capability development (Coombs et al., 2020; Cubric, 2020; Keding & Meissner 2021; Collins et al., 2021). Several papers focused on inaccurate industry perceptions of AI perpetuated by media and research overstatements of AI capability (Cubric, 2020), an obscuration of AI limitations due to vendor strategic secrecy (Newlands, 2021), and the dominance of the narratives driven by technology corporations on the unquestionable benefits of AI but are not well supported by research transparency or effective use cases (Bender et al., 2021; Birhane, Prabhu, et al., 2021; Holmstrom, 2022). Several papers noted that tensions and issues in research outputs on AI capability often stem from the proprietary and profit motive nature of the significant quantity of research emanating from technology corporations. Criticisms include misleading narratives of AI capability, systemic overselling of AI capability, the lack of quality control in machine learning, and bypassing the peer review process so that research claims are not open to public scrutiny and critical review (Marcus, 2022; Birhane et al., 2021a; Newlands, 2021; Bender et al., 2021).

The category of ***governance and ethics*** contained themes related to the importance of organisations navigating the complex field AI ethics and governance issues. Several papers in this category raised the importance of AI governance and ethics as a key responsibility for organisational leaders and regulators to maintain AI efficacy and ensure public safety from AI harms. While there is growing interest in AI ethics within the research community as well as in technology companies, there is widespread belief that it lacks effective reinforcement mechanisms citing key trends where technology companies deviate from their codes of ethics without consequence which fuels public distrust and skepticism (Birhane, 2021; Hagendorff, 2020; Newman et al., 2019). AI ethicists still believe that AI holds significant potential to improve many aspects of human life and business value creation, however they also caution that AI also poses major systemic threats and harms such as bias, discrimination and safety (Floridi et al., 2018; Hagendorff, 2020; Morley et al., 2021; Taddeo & Floridi, 2018); elements that can potentially destroy value.

Researchers believe that a solid ethical AI framework is necessary and should not be seen as a limitation, but as a tool to help harness and shape AI potential to create value in a constructive and sustainable manner (Giuliano, 2020; Taddeo & Floridi, 2018). While technical ethical "fixes" can be found for specific problems, such as accountability, privacy protection, anti-discrimination, safety, or explainability (Giuliano, 2020; Hagendorff, 2020; Shin, 2021; Taddeo & Floridi, 2018) there are still considerable knowledge gaps when it comes to AI ethics and governance of system design and machine learning models that require more research, as does more discerning models of AI technology implementation and management.

From these findings we derive **Research Position 1: Strategic technology leadership.** Organisations require strategic technology leadership informed by objective, fact-based intelligence on value creation potential and governance frameworks. How might we develop proactive leadership in the strategic positioning of AI enabled organisations?

3.2 Human engagement

The human engagement focused on the understanding of the psychological, sociological, neurological and biological factors that affect how humans engage, interact and collaborate with AI, and that many of these challenges are unique to intelligent technologies. There are two key categories that dominated the literature in this cluster are human engagement and motivation and human-machine interaction.

It was widely reported that ineffective human centred design was a key obstacle in ***human engagement and motivation*** in working with AI technologies (Borges et al., 2021; Collins et al., 2021; Cubric, 2020;

Enholm et al., 2021; Langer & Landers, 2021; Rzepka & Berger, 2018). Some of the engagement and motivational design elements that were highlighted include: Human-like design features of AI systems or anthropomorphism that includes of the looks and gestures of robots, as well as the voice, expression, and conversation of virtual agents such as chatbots or virtual assistants (Rzepka & Berger, 2018). Other design elements included the adequacy of system transparency and explainability (or dealing with the blackbox problem) that is built into the interactive design aspects, information flows, and task allocation. When well designed, these elements contribute to engendering greater levels of user trust and acceptance and dissipate fear and negative emotions (Enholm et al., 2021; Langer & Landers, 2021; Shin, 2021; Hemmer et al., 2021; Adadi & Berada, 2018).

The literature suggests that without deeper insight and understanding of human engagement and motivation AI-based decision support systems face accuracy and efficacy issues due to the barriers they create for human-AI collaboration (Smorodinskaya et al., 2017; Xu & Yu, 2020; Xu, 2019). Solutions stem from deeper and philosophical perspectives that require industry-wide effort on the development of an improved language that better articulates the new world skills and capacity required of a human-machine collaborating team (Carroll et al., 2019; Seeber et al., 2018; Crouser & Chang, 2012), to models of a machine theory of mind (Rabinowitz et al., 2018), as well as human theory of mind (Baker et al., 2011; Stowers et al., 2021) that will contribute to improved interaction and decision making for both machines and humans required for the long term (Akata et al., 2020; Stowers et al., 2021).

In the ***human-machine interaction*** category, it was reported that new autonomous systems require intelligible interfaces to ensure that skilled workers are able to *understand* how the technology may affect them, *trust* its information and feedback, and feel in control of the decision-making process (Abdul et al., 2018; Adam et al., 2018; Akata et al., 2020; Grønsund & Aanestad, 2020) and even apply novel interfaces that support interactive, open-ended explorations (H. Liu et al., 2021; Q. Liu et al., 2018). Several papers identified a need to move away from traditional approaches to technology design and adoption that seek to "optimise humans" (which is based on a utilitatian position of a rational use of resources) towards more nuanced and complex cultural and emotional aspects of human-machine interaction (Frauenberger, 2019; Jarrahi, 2018; Zhuge, 2020).

Derived from these findings, we offer **Research Position 2: Human-centered AI enablement.** Human engagement and motivation are critical to developing the human potential side of the augmented intelligence equation. How might we incorporate the requisite human-centered perspectives and tools that enable AI technology acceptance and value creation?

3.3 Organisational evolution

This cluster highlights the role of building enabling organisation systems, structures, processes and networks that are conducive to effective human-AI technology acceptance, adoption and collaborative teamwork. It includes two key categories of systems enablement and reconstructing work design.

From a ***systems enablement*** perspective, there is widespread agreement that AI systems should be considered socio-technical systems that co-evolve with their users (Enholm et al., 2021; Niehaus & Wiesche, 2021; Rzepka & Berger, 2018). This provides for a more dynamic approach to AI design and deployment in an environment dominated by rapid technology development and socio-economic change (Crouser & Chang, 2012; Grønsund & Aanestad, 2020; Lundberg et al., 2021; Methnani et al., 2021; Yang, 2021). It is already widely accepted in information systems research that the socio-technical nature inherent in information systems means that technology innovation is inseparable from the social processes of organizational development and change (Augerou 2003). However, when viewed critically, AI research to date has focussed predominantly on the emergent technologies and the value creation opportunities they represent, and less so on the human, organisational and social aspects.

Several papers advocated the concept of *innovation ecosystems* as a more appropriate approach to AI systems development and management. Innovation ecosystems are fundamentally *complex adaptive systems* that emerge in the course of collaboration among networked actors (both human and machine) to co-create value (Chan, 2001; Newlands, 2021; Smorodinskaya et al., 2017). This raises the question of whether the socio-technical systems are sufficiently flexible and dynamic enough in their architecture to nurture the development of innovation ecosystems that are essential to support human-AI collaboration and co-creation. However, both approaches take a systems-based view on value creation.

From a ***work design perspective***, function or task allocation in augmented and collaborative human-machine systems needs to be dynamic rather than rigid or prescriptive. Increasing computational power is constantly shifting the boundaries of technological and human capability and the nature of work itself, and all this within increasingly complex and ill-defined problem spaces. Furthermore, human oversight in the decision-making process, user inclusion in the overall system design, work design and performance evaluation lead to better operational outcomes for specialist augmented functions (Borges et al., 2021; Crandall et al., 2018; Langer & Landers, 2021; Fügener et al., 2021; Grønsund & Aanestad, 2020; Lundberg et al., 2021; Keding & Meissner 2021). This requires moving away from traditional or hierarchical 'human resource' approaches to work design and management, towards more novel or democratised approaches that facilitate more harmonious human-machine co-operation (Crouser & Chang, 2012; Langer & Landers, 2021; Methnani et al., 2021; Crandall et al., 2018; Fügener et al., 2021). This also provides for greater perceived transparency, fairness, and a human influence in creating and maintaining meaningful employment (Parent-Rocheleau & Parker 2021; Marabelli et al., 2021).

We offer **Research Position 3: Dynamic workplace systems and structures.** AI value creation requires the adoption of dynamic organisational ecosystems approaches where human-machine collaboration can flourish. How might we proactively evolve and adapt organization systems and structures to enable AI value creation goals?

3.4 Technological development

This cluster focuses on the limitations and potential of AI technology design, data models and algorithms in facilitating human-machine collaboration. The three key categories within the technology cluster are AI acceptance complexities, algorithmic behaviour, and next generation cognitive technology.

In terms of ***AI acceptance complexities***, it was widely agreed that the 'human-like' intelligence inherent in AI technology triggers a more complex psychological pathway that humans need to navigate in order to accept AI as a team member and collaborator. AI represents an extension of humans rather than a simple utilitarian tool (Ajenaghughrure et al., 2021) and this fundamental difference means that technology acceptance models (and technology design) need to adapt and incorporate greater emphasis on elements such as hedonic motivation, social influence, anthropomorphism and emotion (Gursoy et al., 2019; Lu et al., 2019), personal innovativeness (Fan et al., 2020) and even a fascination for technology (Sohn & Kwon, 2020). AI technology acceptance issues go beyond the utility of the technology into complex psycho-social factors that affect users such as fear (Cabrera-Sánchez et al., 2021), AI Anxiety (Lee et al., 2021; Oh et al., 2017; Wang & Wang, 2019), algorithm aversion (Dietvorst, 2015), bias and mistrust (Ishowo-Oloko et al., 2019) and wilful lack of co-operation (Kiesler et al., 1996). The difference with AI relative to other information systems is that humans interact with algorithms and cognitive agents, not just interfaces (Oh et al., 2017) which trigger human expectations of social identity, relational or commitment norms (Castelfranchi & Tummolini, 2003; Ishowo-Oloko et al., 2019; Kiesler et al., 1996).

At the core of human-machine co-operation is the ***design and coding of algorithms*** and machine learning models that support collaborative interactions. In true collaborative environments, AI enabled technology needs to be sensitive to human intuition, cultural norms, emotions, social signals and pre-evolved dispositions that support and extend the ways humans reason in decision-making (Carroll et al., 2019; Seeber et al., 2020; Cooke et al., 2013; Jarrahi, 2018; Dellerman et al., 2019; Fugener et al., 2021). While such deliberately designed algorithms have been shown to produce good co-operation levels between human-machine and machine-machine at comparable levels of human-human cooperation (Carroll et al., 2019; Crandall et al., 2018), researchers found that these algorithms are difficult to come by as most have been developed and trained to compete and defeat humans rather than co-operate with them (Adadi & Berada, 2018; Crandall et al., 2018; van den Hoven, 2007).

Solutions lay in thoughtfully designed reinforcement learning algorithms based on human-machine collaboration trained on supportive datasets (Carroll et al., 2019; Stowers et al., 2021) as well as an evolved theory of mind for both human and machines which is seen as essential for complex decision-making environments (Akata et al., 2020; Baker et al., 2011; Rabinowitz et al., 2018; Singer & Tusche, 2013). However, several papers in our review maintained that development of more collaborative algorithms will be constrained by the limitations in current quality and veracity in data sets and machine learning models (Chen et al., 2018; Newlands, 2021; Birhane, 2021, Crandall et al., 2018; van den Hoven, 2007; Scheuerman et al., 2021). Without a fundamental shift in how datasets are curated, algorithmic behaviors will be predicated on the past such as limiting human stereotypes, predominant mental models, bias and values. This speaks to the wider general problems persistent in the machine learning domain which has become a recurring theme in our review, where a lack of systematic and structured methods and processes to develop, deploy and evolve models (John et al., 2022) results in AI often exhibiting poor behavior when deployed in the real-world applications (D'Armour et al., 2022).

In the category of ***next generation of AI technologies,*** we grouped together three concentrations of papers that appeared central to how AI technologies can redefine the future development of more humanistic and collaborative AI systems. The three topics in this category included are cognitive computing systems, creative AI systems and values sensitive design.

It's argued that the field of *cognitive computing systems* will drive the next generation of AI technologies that will enable better collaboration and teamwork with humans due to greater inclusion of emotional and relational aspects into AI design that will improve communication, co-ordination and interactivity (Dong et al., 2020; Duan et.al. 2019; Chen et al., 2018; Schuetz & Venkatesh, 2020). The emergence of cognitive computing has enabled the development of a variety of technologies that leverages cognitive science to build an architecture of more advanced AI subsystems. These incorporate machine learning, NLP, computer vison and human-computer interaction (Schuetz & Venkatesh, 2020; Duan et.al. 2019). *Creative AI systems* featured highly in this cluster. Creative AI also known as computational creativity is defined as a subfield of AI research that builds computational systems that produce collaborative creative artefacts such as music, artwork, games, literature and design (Rezwana & Maher, 2022; Guzdial & Reidl, 2019; Teresa et al., 2020; Colton & Wiggins, 2012) that offer learnings for the creation of applications for information systems. This positions the creative AI as an emergent intelligent creative partner that shares a joint creative goal with humans (Guzdial & Reidl, 2019) and is consistent with the findings on the importance of collaborative, adaptable and self-learning bi-lateral systems of human-machine symbiosis (Charnley et al., 2012; Cook et al., 2019; Teresa Llano et al., 2020).

An important field that emerged in our review was the use of ethically aligned co-design methodologies throughout the design phases of intelligent AI systems (Leikas et al., 2019; Zicari et al., 2021). The use of *value sensitive design (VSD)* was frequently mentioned as a key methodology to this aim (Liao & Muller, 2019; Umbrello & de Bellis, 2018; Umbrello & van de Poel, 2021). VSD is defined as a theoretically grounded approach to the design of technology that accounts for human values in a principled and comprehensive manner throughout the design process (Friedman et al., 2013). The importance and relevance of VSD is underpinned by the argument that information systems are intentionally or unintentionally informed by moral values of their makers (van den Hoven, 2007). Several papers provided case studies that adopted a design philosophy that embedded values into the design of artificial agents at the early stages of AI development, largely driven by the high-risk stakes of unmitigated AI design (Umbrello & de Bellis, 2018; Longo et al., 2020; Riebe et al., 2020). The papers argue that by incorporating universal human values in AI design assists in managing the current challenging areas in the domain of transparency, explicability, accountability and bias. Several papers provided conceptual AI technology design frameworks to this end (Leikas et al., 2019; Robertson et al., 2019; Umbrello & de Bellis, 2018; Umbrello & van de Poel, 2021; Zicari et al., 2021).

We offer **Research Position 4**: **Values-based AI technology architectures.** Advancements and limitations in machine learning, cognitive computing and computational creativity are outpacing organisational capability to realize AI value creation opportunities. How might we develop renewed technology architectures adapted to the unique challenges and opportunities of augmented intelligence?

3.5 Discussion

In addressing our research question of *What are the key enablers of organisational value creation for augmented intelligence?* we reflected on the composition of the thematic clusters, categories, and the detailed themes behind them to construct meaning and an overarching story from the data. After several iterations we derived a conceptual framework that highlights the interdependency and co-ordination of strategic leadership, human engagement, systems adaption and technology development as enablers of value creation. The literature we reviewed placed emphasis on building technologies synergise with human motivation, engagement and interaction, and on imbedding those technologies within renewed organization systems and processes. Findings in the technology component in our findings emphasize that while the considerable potential of AI technologies is clear, a renewal and realignment of technological capability is required to enable human-machine collaboration to its full potential. This requires an investigation of new generation technologies and improving the current limitations and potential performance of machine learning.

A further reflection of the technology cluster shows that it appears to be somewhat fragmented, however this is a reflection of the state of research in the domain as we have uncovered in this review. This highlights the importance of the strategic leadership cluster on it's important role in combining and aligning these key components into a coherent organisational approach to strengthen value creation from human-AI collaboration. To this end we identified an overarching theme as the common denominator between the key enablers of value creation and how they interact and influence each other. We herewith conclude with **Research Position 5: Strategic alignment and multidisciplinary approach** that focuses on how might organisations strategically align their socio-technical systems to enhance human-AI system development and implementation?

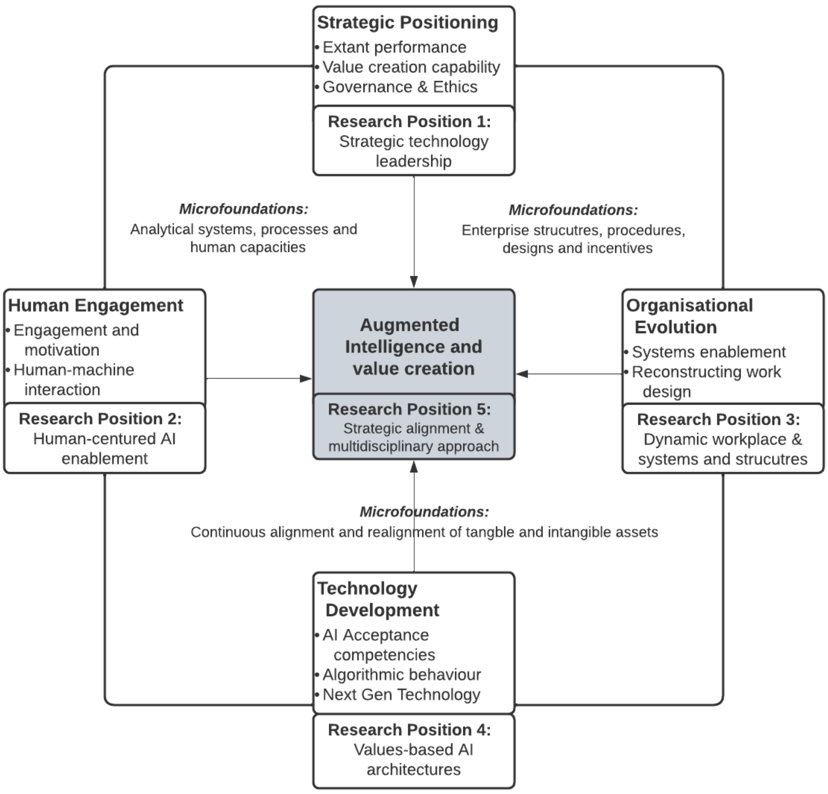

Figure 2. Conceptual framework: Factors enabling value creation in augmented systems

However this conceptual framework needs to be imbedded within a wider organizational context and legacy systems. We reflected on the requisite microfoundations of enterprise structures, systems and processes that provide the architecture to imbed the enablers of value creation in augmented systems. Informed by Teece (2007) we further developed on our conceptual framework to provide a microfoundations perspective on enabling value capture, which in themselves offer opportunities for further research. The Dynamic Capabilities Theory (Teece & Pisano, 2003) is a long-standing framework used in strategic management and the related framework of microfoundations (Teece, 2007; Palmier & Parida, 2022) emphasize the need of organisations to constantly adapt, integrate, and re-configure organizational skills, resources, and functional competences particularly in rapidly changing technological environments.

Value creation from augmented intelligence may depend on the inherent dynamic capabilities and microfoundations of each organization to translate opportunities into tangible outcomes. While clear enablers of value creation from augmented systems have been identified in our review, to realize value from AI organisations may need to leverage complementary resources and microfoundations (Mikalef et al., 2021) or practice greater alignment of control points along their digital ecosystems (Pagani, 2013). In our framework, we have incorporated the microfoundations (Teece, 2007) of *Analytical systems, processes and human capacities* to enable our cluster of human engagement. Similarly, Teece's microfoundations of *Enterprise strucutres, procedures, designs and incentives* to enable our cluster of organisational evolution and *Continuous alignment and realignment of tangble and intangible assets* to enable technology development. Using a microfoundations approach deepens our theorization of how organisations can realize value from augmented intelligence and opens opportunities for further research and practice.

Limitations of our research lies in three key areas. First, the nature of our methodology limits the breadth and depth of literature that is included in our search and analysis, and we have tried to counteract this with a significant forward and backward searches. Secondly, unintended researcher bias is also a risk factor in any thematic analyses that are undertaken as they often speak to the internal biases of the researcher stemming from their innate world views. We note the similarity in the groupings of our thematic clusters are similar but not exact to the four elements of socio-technical systems theory. Finally, we also acknowledge that the theoretic foundations of dynamic capabilities and microfoundations assist with grounding of the enablers identified in this review, they also potentially contain theoretical limitations to their applicability the domain of augmented intelligence. The field's interdisciplinary development outside of computer science and engineering domains is only recent, and this and opens opportunities for further research in the domain of augmented intelligence.

4 Conclusions

Research into the next generation of augmented human and artificial intelligence is in the early stages of development, particularly in the specialised area of human-machine collaboration in complex environments. The field is challenged by research fragmentation, a lack of generalisability of results across research and application domains, systemic challenges with algorithmic models and limitations in machine learning training data, a lack of critical research on AI capability for value creation and pressing ethical challenges that have been inadequately addressed. The potential benefits of AI technologies are undeniable however they are still largely underdeveloped and require the maturity that more multidisciplinary approaches may provide. Research points to the reality that value-creation may be in the human, organisational and strategic ecosystems that supports and utilises AI technology rather than in the technology itself.

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Appendix 1: Thematic Analysis Summary: Clusters (4), Categories (10) and themes (75)

Clusters (4)	Categories (10)	Themes (75)
Human Engagement	Engagement and Motivation	Innate, irreplicable human skills, therefore need augmentation Meaningful human engagement and work Cultural emotional aspects of AI Inconclusive and inconsistent results Situational contexts determine outcomes Intimate entanglement & boundary fuzziness Psychological, biological, neurological impact AI system transparency, explainability, interpretability Job security, safety, fear, trust Stakeholder engagement, consultation & involvement
	Human-Machine Interaction	Human-centred design; usability & interpretability of interfaces Human-computer interaction design Collaboration and teamwork in the age of AI AI intelligences types & uses Intelligible interfaces and systems Anthropomorphism influences Human autonomy, oversight & control in decision making Impact of personal effectiveness, innovativeness in interaction
Organisation Evolution	Systems Enablement	Socio-technical systems approaches Innovation ecosystems approaches Complex adaptive systems approaches Approaches to systems design; value is in the ecosystem
	Reconstructing Work design	Augmentation as a spectrum and also present in automation Humans in the loop (goals, roles and value) Computation vs collaboration design Dynamic configurations of tasks and functions Autonomy and trade-off choices Power asymmetries influences Participatory processes for better design and technology acceptance Meaningful work for human-AI configurations Human autonomy, oversight & control in decision making
Strategic Positioning	Extant Performance	Decision making effectiveness in computation & data analytics design Decision-making effectiveness show mixed & inconclusive results Behavioral effects of human-AI decision-making process Lack of confidence in AI-led decisions Management over-confidence & overreliance on AI decisions AI aversion Vs AI appreciation – context is critical Active & collaborative participation in AI performance evaluation New models of business practices and management required New cultural practices required – cultural reshaping
	Value Creation Capability	Sub-optimal investment in AI Returns underrealized in general from AI Automation ROI significant

Clusters (4)	Categories (10)	Themes (75)
		Most business value through automation rather than augmentation
		Unclear how value is created with AI technology
		Pilots and experiments dominate, and don't translate well into real world
		Lag indicators from R&D to implementation requires long term view
		Returns, values and potential overstated
		Research fragmented and not generalizable
		Strategic positioning and choices require clarity
		Managerial capability, learning & adaption
		Worker capability development, learning & adaption require focus
		Organisational capability adaption & evolution
	Governance and ethics	Ethics, harm and safety at the periphery
		Systemic bias & replication of the status quo
		Public awareness, inclusion and debate
Technology Development	Technology acceptance	Organisational environments & culture influence technology design
		AI system transparency, explainability and interpretability are critical
		Complex psychological pathways to navigate with AI technology
		AI as an extension of humans rather than a tool – psycho-social effects
		Limitations/extensions of traditional technology acceptance models
		AI technology acceptance frameworks required
	Algorithmic behaviour	The black box problem and its impact on trust & explainability
		The data problem – training data limitations
		ML models – require more innovative methods or reproduce status quo
		Bias for competition over co-operation in training models; design choices
		Reinforcement learning models based on teamwork and co-operation
		Algorithmic aversion Vs appreciation
		Ethics and governance require more attention
	Next generation AI cognitive technology	Ethically aligned co-design methods needed
		AI design frameworks – build in humanistic features from start
		Rise of human-centred cognitive computing
		Cognitive computing systems to improve AI subsystems
		Creative AI systems and computational creativity – learnings
		Value sensitive design – universal human values as a design tool
		Key References: Alahmad & Robert, 2021; Chen et al., 2018; Dong et al., 2020; Ochs et al., 2017; Colton & Wiggins, 2012; Teresa et al., 2020a; Teresa et al., 2020b; Teresa Llano et al., 2020; Vogeley, 2010; Foster et al., 2017; Kim et al., 2017; Operto, 2019; Trejo, et al., 2018; De Momi et al., 2016

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