COGNITIVE AGILITY FOR IMPROVED UNDERSTANDING AND SELF-GOVERNANCE: A HUMAN-CENTRIC AI ENABLER

Abstract

Artificial Intelligence (AI) is a catalyst for innovation activity. This chapter looks at developers and entrepreneurs as key human actors forming a performance triad with the AI. Successful exploitation of AI capabilities in entrepreneurial contexts requires humans to successfully collaborate, prevent communication errors and maintain control over the AI. To achieve this, human enablers require cognitive agility. This skill is founded upon metacognition and relies on heightened domain cognisance and the ability to govern one's own actions. These attributes can be trained through adaptive non-standards based forms of education. Failure to develop the necessary human factor attributes risks increasing the likelihood of compromising the triad and the catalytic effect of AI. Developing cognitive expertise can mitigate ethical issues, power imbalances, bias, and adversarial factors that present significant challenges to technological solutions.

Keywords: cognitive skills, artificial intelligence, human-centric, cognitive agility, expertise, entrepreneur

INTRODUCTION

As a general purpose technology (Cockburn et al., 2018), Artificial Intelligence (AI) and its sub-category technologies are advancing societal and business opportunities as they augment human innovation performance (von Krogh, 2018). AI algorithms can harvest and mine unfathomable amounts of digital data from cyberspace enabled online platforms such as social media, online markets and connected devices (IoT) to support human creativity, intuition, decision-making and risk taking. The disruptive potential of AI and its associated technologies lower the bar for nascent entrepreneurs to venture and grow. By reducing inherent uncertainties relating to entrepreneurship and predicting ways of dealing with uncertainty (Nambisan, 2017), AI is a catalyst for entrepreneurs to identify, develop, and exploit opportunities (Shane and Venkataraman, 2000).

Technologies that push innovation efficiency frontiers in ideation, market research, advertising, production, distribution and achieving desired effects underscore entrepreneurial success by bolstering the fundamental human desire to create. The opportunities for the good of mankind are seemingly endless. So too are the indicators of the potential transcendence of humanity if we do not keep the AI systems under our control in the short-term, before it controls us (Hawking et al., 2014). A necessary step then is to address the intersection where a) AI's digital technologies meet b) the people with the expertise to design and develop them, and c) the entrepreneurs who seek to use the intelligent algorithms for their immense potential in the pursuit of gaining some form of advantage. The unique characteristics of these three domains, and how each brings its own unpredictability and non-linearity to entrepreneurial pursuit, challenge the boundaries of the entrepreneurial process (Nambisen, 2017). This triad inspires and facilitates more collective ways of pursuing entrepreneurship (Kim and Aldrich, 2007) in for example crowdfunding (Mollick, 2014) and through social media platforms (Fischer and Reuber, 2014).

In a period of constantly advancing digitalization of entrepreneurial activities, the human cognitive skills required for the design and the end-users application to fully leverage entrepreneurial opportunities demand closer attention. Improving our understanding of how we engage with the new opportunities AI provides to entrepreneurs can make us more aware of the implications this technology has for the required cognitive skills of humans involved in developing and using AI. Doing so, can lead to a better chance of avoiding communication errors between the experts developing the AI technology and the entrepreneur as its user. For now at least, for AI to unlock variations in business models that enable the reordering of business processes for economic advantage; or automating predictive capabilities to reduce R&D costs and accelerate the time it takes to get a product to market, there remains a significant human-to-human element.

An example of where AI is providing game changing capabilities is in the rapidly expanding cybersecurity industry. AI is supporting how organisations protect networks and systems from cybercrime that is estimated to cost upwards of $6 trillion annually by the year 2021 (Cybersecurity Ventures, 2017). This example shows the current approach where AI solutions form part of a human-machine team. The AI enables intelligent enterprise through human-machine collaboration, supposedly allowing the human to "focus on higher-value work" (Mueller, 2020). Ensuring this powerful learning machine remains collaborative demands attention to when this 'higher-value human work' should occur, and what cognitive competencies are needed to add value, when algorithmic actions are based on complex rules that challenge or confound human capacities for action and comprehension (Mittelstadt et al., 2016).

For entrepreneurs to lead innovation and ensure that AI's capacity to solve real world problems and bring benefits for all, increasingly means being able to combine knowledge of the algorithms with an understanding of functional goals (Canning, 2020). This holistic understanding takes cognitive agility to expertly handle the positive and negative potential of AI in the domain of application. Pedagogic development of the appropriate human regulatory tools could ensure the seemingly endless positive possibilities of ML algorithms do not blind or cloud judgements. There is an entrepreneurial risk - moral, legal, ethical, and financial - when underlying algorithmic design and configuration are themselves value-laden (Brey and Soraker, 2009; Wiener, 1988) privileging certain values and interests ahead of others. The once held belief that machines do not display bias and are ideal neutral decision makers is unsustainable (Mittelstadt et al., 2016). Not acting to improve cognitive skills only contributes to strengthening the likelihood of the algorithmic "black box" holding all the power (Pasquale, 2015).

This chapter proceeds by profiling the developers, entrepreneurs and AI before considering the cognitive demands placed on the first two when having to perform in a context where the third is the master. Further, the need for developing the cognitive skills of domain cognisance and self-governance across divergent disciplinary fields of expertise is presented and discussed. Such skills are needed to avoid maladaptive behaviours hindering innovation activities. Finally, an education approach is suggested that can support building the required understanding and governance mechanisms to ensure the human remains the AI enabler as a result of cognitive agility.

THE HUMAN IN THE DRIVING SEAT

The current performance pathway of AI is determined and enabled by humans. Entrepreneurs introducing AI capabilities that can anticipate what people perceive and need, based on information consciously or unconsciously made available is a risk laden activity, especially in a context where governance mechanisms are playing catch-up. Three distinct but complementary human factors capable of ensuring human agency maintain a semblance of control and remain in the AI driving seat are: metacognition, domain cognisance and self-governance.

Metacognition describes a level of consciousness when judgment and appropriate initiation of change of cognition or action/behaviour becomes optimal. If an individual uses metacognitive strategies, they have the ability to understand, control, and manipulate their own cognitive processes' (Meichenbaum, 1985). It is the art of being aware of and exerting control over one's thinking to achieve present goals.

The idea of self-governance is founded upon advanced understanding gained through metacognitive skill development. Governance-of-self in an AI innovation context recognizes a legitimate effort to make events involving human-AI interaction happen in a productive direction. It allows for governance to be understood as a practice capable of occurring at lower levels in entrepreneurial endeavors. For entrepreneurs and developers to avoid psychological traps that can lead to, for example, communication errors, they should have well developed self-governance based upon educated and trained cognitive capacities that are known to support performance. Entrepreneurs and developers become more self-aware (knowing their strengths and weaknesses), better at assessing task demands, evaluating their knowledge and skills, can plan approaches, monitor progress and make appropriate situational adjustments (Ambrose et al., 2010). Consequently, metacognitive skills can improve the individuals' situational awareness and thus increase the chance of better performance; as improved situational sense-making leads to better situational leadership (Northouse, 2015), meaning the ability to lead and direct themselves, based upon enhanced understanding and piloting of own behaviour as a result of better domain cognisance.

Just as important as having the ability to understand and simultaneously use multiple cognitive strategies to govern one's own behaviour, is that of achieving a greater understanding of the domain one operates and collaborates in. Being more cognisant can support achieving desired outcomes, accelerate expertise and improve praxis (Ward et al., 2013). The concept of domain cognisance describes an elevated level in the function of understanding (UK Ministry of Defence, 2015). From a performance perspective, this challenges the practice of extending one's current knowledge, whilst facilitating the acquisition of new knowledge and reasoning competencies, at the edge of current cognisance (Ward et al., 2018).

PROFILES

Consideration of the profiles of AI, developers and entrepreneurs reveals a constellation of complex characteristics. Acknowledging the traits and identifying ways to leverage the positive aspects of each, can mitigate negative outcomes as points of friction arise due to psychological and developmental vulnerabilities impacting innovation performance.

The AI Profile

Interaction with AI technology includes processes such as decision-making on a) areas of application (which question do we want to have answered?), b) decisions on to what extent results will be implemented or modified and seen as an informative or determining tool, c) decisions on how to communicate potentially controversial outcomes of AI processes to all stakeholders and the question of internal or public acceptance of decisions based on AI inclusion.

It is common to identify someone who successfully solves novel problems as being intelligent, as to do so takes creative logical thinking. This type of intelligent functioning, being able to handle a problem one has not seen or dealt with before, is a function that AI is currently not good at. AIs profile is one of a specialist agent anchored to existing data that has difficulty creating effective solutions in uncharted waters. Until AI can function effectively in the environment where it helps solve novel tasks and has the agency to act alone in a complex context where new challenges are regularly presented, it will still be viewed as a tool instead of an independent agent (Panova, 2017).

For AI to be fully accepted into the decision-making process, it needs to be positively perceived. While AI is purely technical and objective in its procedures, human perceptions and evaluations can influence how AI is used. When the AI has been developed to be transparent, with reliable algorithms and instant outputs, then it is cognitively perceived with trust, but this can be influenced by more emotional based processes that can be connected to personality aspects (Glikson and Wooley, 2020). The more a human can connect to the intelligent system the quicker the person develops an emotional trust to the system. In other words, if the AI can affect higher order cognitive processes associated with rational decision-making as well as more intuitive emotional based decision-making processes, then the AI will be seen as trustworthy and valid.

The Developer Profile

Humans with highly developed technical skills develop AI for users with different professional, personal and motivational backgrounds. AI's function to provide superior or additional decision-making opportunities requires the potential to disrupt where necessary established human habits, tendencies and biases. The maximization of AI potentials requires highly efficient perspective-taking and resulting shared mental models between the developer and the end-user entrepreneur. The developers performance encompasses not solely the provision of an AI that fulfills the entrepreneurial needs representing a rather pragmatic and technical value, but also includes the development of a technology producing results that are meaningful, accepted and factually implemented.

The creation of AI technology can thus not be seen isolated from the psychological context in which AI development happens. Research on the personality of developers is scarce. However, available scientific evidence can provide some information pointing at resources and limitations that lie in the developer's personality, with direct impact on the end product and consequently its actual applicability. Psychological research obtained data indicating that openness to new experiences - a trait of particular relevance for the adaptation to individual and diverse user needs - is more pronounced in more experienced senior staff (Licorsih and MacDonnell, 2015). Research further indicates that developers become more conscientious over time as they age and gain more experience, but that they tend to become less agreeable (Rashtogi and Nagappan, 2016). These psychological traits can be resources (high degree of openness) as well as challenges (low agreeableness) when it comes to designing AI solutions with a high level of customer-orientation, and thus perspective-taking in regards to psychologically diverse and sometimes challenging entrepreneurial personalities. Gender differences also exist that can influence the development process and the resulting AI performance. As an example, male developers have been shown to display more narcissism and consequently more difficulties with team-work and perspective taking (e.g., Russo and Stol, 2020). Other evidence shows characteristics related to interpersonal challenges in regards to team performance and collaboration (Blickle et al., 2018). Female developers, on the other hand showed more honesty-humility traits contributing to better work performance (Johnson et al., 2011). Female developers are more likely to display emotional instability, but may compensate this with better team performance and collaborative skills (Russo and Stol, 2020). While it should be underlined that these findings reflect group averages and do not allow for direct conclusions on an individual basis. The personality profiles of developers suggest personality patterns with relevance for the interpersonal aspects of the developmental process, besides purely technical skills.

The Entrepreneur Profile

In relation to the developed AI, the entrepreneur's role is to assess the information the AI produces and integrate it into their decision-making. Innate tendencies of the end-user can interfere with objective understanding of the purpose of developing the AI and how the AI's information can be used. Entrepreneurial profiles can influence the perceptions of AI. For example, higher extraversion is associated with more risk-taking. This could help view the AI as a tool that can support them in their decision-making by increasing their confidence. On the other hand, their low agreeableness can make them suspicious of AI's capabilities and contributions. This may cause reluctance to use the AI where it would be in conflict with their own intuitions.

The psychological profiles of entrepreneurs have been mapped on the common "Big Five" model describing complementary characteristics mostly used to outline individual personality profiles known to be rather stable across situations and time. This characterizes the entrepreneurial personality as being high in extraversion, conscientious, and openness to new experiences, while low in agreeableness and neuroticism (Obschonka and Stuetzer, 2017). This constellation is associated with success in their entrepreneurial intentions (i.e. financial indicators, productivity, survival; Zhao et al., 2010).

Entrepreneurs show stronger tendencies of extraversion and dominance (Obschonka and Stuetzer, 2017; Palmer et al., 2019). Extraversion is the state of primarily orienting oneself to exogenous stimuli to guide behavior which entails dominance, excitement seeking, gregariousness, and positive emotion among others. Dominance is comparable to social self-esteem, social boldness, gaining and maintaining status, and goal achievement. Stereotypically, people with these traits are referred to as the 'alpha male', but with a more objective orientation (i.e. goal achievement) rather than social domination (Palmer et al., 2019). Leadership dominance has also been identified as a predictor of organizational achievement (Hoffman et al., 2011). Dominant traits in entrepreneurship are likely to help the management of unsettled environments by eliminating uncertainty and adding perceived control.

Entrepreneurs also score high on conscientiousness. This is the trait of being careful or diligent and implies a desire to do a task well, and take obligations to others seriously by being efficient, organized, and striving to meet desired goals. They can be workaholics, perfectionists, and compulsive in their behavior (Carter et al., 2016), and while these traits are usually associated with negative outcomes in other domains, for entrepreneurship and innovation, these factors have predicted positive outcomes. High scoring openness traits involve imagination, exploration, intellectual interest, and tolerance to ambiguity. These traits help entrepreneurs navigate new ideas and situations, whilst simultaneously managing unknown factors and adjusting to include them into their decision-making (Palmer et al., 2019).

Additional psychological traits that have been identified for entrepreneurs are a high need for achievement, a perception of being in control, and risk-taking propensity. High entrepreneurial self-efficacy has also been predicted in performance outcomes. Entrepreneurs, high in self-efficacy, alongside the dominance trait, had better firm performance (Obschonka and Stuetzer, 2017; Palmer et al., 2019). Lastly, traits or characteristics can be explained through other psychological processes such as role modelling. Entrepreneurship can be passed on as a family tradition and has been identified as a driver for success (Altinay et al., 2012). Also, entrepreneurs score low on agreeableness, a predictor usually found in organisational performance (Zhao et al., 2010).

Interpreting the Mismatch

The AI, developer and entrepreneur triad reveals potential human-centric vulnerabilities that could compromise innovation success. Across domains, agreeableness and the introversion-extraversion dimension have been identified to be specifically relevant for social interactions and can be mapped with the interpersonal circumplex dimensions of dominant—submissive and agreeable—cold-hearted (Wiggins and Trapnell, 1997). The developer-entrepreneur dyad has already some mismatches in their personality constellations. Where as developers are more introverted and submissive-agreeable, their entrepreneurial counterpart is extraverted and not necessarily high in agreeableness. In addition, their need for dominance will be evaluated negatively by introverted developers since they are more sensitive to interpersonal personality traits than their extraverted entrepreneurial counterparts. Their impressions and person evaluations will negatively influence any subsequent evaluation and interactions with others. Introverted developers are generally lower in assertiveness than extroverts (Bendersky and Shaw, 2013) and are likely to detect disagreeable situations earlier and view them as problematic, making them more compliant and less engaged when confronted (Erez et al., 2014). This can be counterproductive in the innovation process since the entrepreneur is reliant on trust, honesty, and cooperation. While it seems that the dominant-submissive fit of the entrepreneur-developer traits would be compatible, this relationship can be negatively perceived by more submissive developers (Moskowitz et al., 2007). Thus, two competing outcomes are present in the process: the introverted developer's preference for relational satisfaction, contra the entrepreneur who may sacrifice interpersonal harmony for the sake of instrumentality (Ames, 2008).

While it seems that the entrepreneurial extraversion trait is better adapted to innovation, introverts have shown to have better decision-making (Khalil, 2016). While entrepreneurs take more risks, are more tolerant to ambiguity, and show high levels of confidence, this does not directly translate to success. Introverts approach their decision-making more systematically, relying on experience, objective information, and think critically about outcomes more than entrepreneurs who are more impulsive. A more symbiotic relationship between entrepreneurs and developers should be preferred. The difficulty in establishing this dyad is that the same traits described above need to be mutually understood and accepted by both parties so that the AI-enabled innovation process can succeed.

An Approach to Leverage Cross Profile Communication Success

Challenges of interdisciplinary collaboration are a well known phenomena. Understanding the constraints, risks, and possibilities associated with communication has undergone extensive research in critical environments such as medical care and aviation (e.g., Entin, 2004; Jacobsson et al., 2012; Mills et al., 2008). As highlighted earlier, the cyber domain is presenting expanding opportunities for AI applications to deter, detect and prevent cyber incidents. The Cyber Domain (NATO, 2016) is also an important domain for studying communication due to the interconnection between networked systems, human actors and virtual agents. A three phase Orientate, Locate, Bridge (OLB) model for teaching and training to help prevent communication errors has been suggested (Knox et al., 2018). This cognitive engineering approach is designed to reduce the risk of negative consequences resulting from miscommunication. Importantly, the OLB model has transferability to the presented context of addressing the communication needs between the entrepreneur and developer dyad.

The Orienting phase is built on the premise that individuals need to monitor and regulate their thinking in hybrid contexts where various conflicting factors converge. It was earlier stated that expert developers and entrepreneurs should think holistically about the AI problem space. This is relevant in the orienting phase as each individual has to be open to extending his/her cognition and modes of communication to ensure a message is accurate enough to be received correctly and understood. Failure here could lead to one or both parties being non-cognizant of issues such as unintended bias in the ML algorithm, or possibly Adversarial ML (AML) supplying deceptive input data (Box 1. presents a summary of how AML has the potential to exploit this human centric vulnerability). Having the metacognitive awareness of factors influencing their momentary mental state, current cognitive processes and trait profile, a communication partner is better able to visualize the most appropriate communication style, method and content to ensure their message is received correctly and understood.

The Locating phase demands an accurate judgement of a communication partner's location in a given, corresponding or alternate context. The point of error here is failure to identify factors that may impact or impair a partner's interpretation of incoming information. Successful locating relies on perspective-taking and acknowledging communication partners needs, as these can ensure more accurate message framing. As described earlier, the psychological profiles and professional goals of the developer and entrepreneur do not intuitively overlap. Meaning perspective-taking can be an effortful act, possibly considered an unnecessary distraction to achieving the immediate entrepreneurial or developer goal. In information societies, it is AI algorithms that increasingly mediate how we perceive and understand our environments and interact with them (Mittelstadt, 2016). The importance of humans as AI enablers means communication failure at this critical locating phase could lead to unexpected issues relating to requests for data transparency, erasure and portability. As international legal frameworks, such as GDPR, attempt to legislate, scrutinise and tame the hiddenness and opacity of ML algorithms (Edwards and Veale, 2017) entrepreneurs and developers need to perceive each other's limits of knowledge, world views, motivations and occupational drivers if together they are to share a holistic mental model of their specific innovation domain, and avoid being held accountable for the inexplicable actions of their AI.

Lastly the Bridging phase requires adaptation of form and content of information. Doing so can lead to a co-constructed shared situational model. Bridging is reliant upon appropriate levels of detail, applying conventional norms and forms of presentation, knowledge about the degree of tolerated uncertainty, situationally appropriate level of confidence, and the openness to admit the need for additional information or simplification (Knox et al., 2018). The need to be adaptive is key in this phase as individuals are often required to self-correct, accommodate communication with more heterogeneous partners beyond a face-to-face dyadic in a socio-technical context.

Cognitive Agility

A concept that has the potential to provide a human performance edge for innovation success is cognitive agility. This thinking capability supports how individuals gain control over their own biases and better prepare themselves to meet their own and other's counterproductive behaviour. Considering the profile challenges presented earlier, cognitive agility can ease individual and collective/collaborative decision making based on various situational factors, whether they present opportunities or constraints.

Specifically, cognitive agility can be understood as an individuals' metacognitive strategy proficiency to meet objectives with situational constraints (Hutton et al., 2020). AI presents multiple situational constraints when it is applied in contexts that demand such things as consideration of physical world implications, ethical dilemmas, legal aspects, strategic and operational level business effects, and adversarial interference. Innovations where the task characteristics require effective coordination between multiple agents and asset types (human, technical, tangible and intangible) to build understanding and expedite collaboration will likely benefit from self-governing individuals with openness, flexibility, and adaptability: the psychological characteristics of cognitive agility (Hutton and Turner, 2019).

It is apparent that entrepreneurs and developers need to function with cognitive agility if they are to be effective across multiple thinking spaces. They need to have an understanding about the benefits and opportunities AI has to offer, whilst also understanding how the other person's personality constellation functions and how this can influence the development process. Metacognition includes the combination of self-awareness, self-regulation and awareness of the role of other actors. Developing metacognition will help decrease time losses due to individual biases, preferences and needs, and avoiding communication failures. In turn this would increase productivity by developing a theory of mind of the other person's approaches based on their personality preferences and cognitive approaches to decision-making (see Conway et al., 2019, for review).

Box 1. AML: Exploiting a Vulnerability

AI has a number of facets that need attention regarding how they are being developed without the necessary legal, ethical, and fundamental safety, security, privacy and transparency considerations (see for example Edwards and Veale, 2017). Not strictly technical, AI challenges such as deep-fakes empowering disinformation campaigns (Chesney et al., 2018), bad data appearing as a result of algorithmic bias (Hu Zhang et al., 2018) and ethical issues in Natural Language Generation (NLG) (Smiley et al., 2017) require entrepreneurs and developers consider how to detect, respond and remediate threats against their Machine Learning (ML) systems. One such feature is Adversarial Machine Learning (AML) that arose as a consequence of developments in AI and ML. AML presents opportunities for advancing positive capabilities for innovation such as reducing data noise for improved algorithmic performance, as well as developing Agnostic AI systems where AML removes inherited ML and Deep Learning (DL) data biases (Hu Zhang et al., 2018). However, AML also has the potential to undermine and disrupt societal systems and critical infrastructure that rely on such *things as trust and data integrity for sustainable and ethically sound performance. Entrepreneurs that fail to scrutinize the security of their ML systems as a consequence of their eagerness to capitalize on AI advancements, for efficiencies and capabilities, risk being deceived or hobbled, not only by their own negligence or haste, but by AI gone bad.*

Practical attacks using AML techniques were first demonstrated by Papernot et al. (2017) who focused on image data and attacked the ML powered image classification algorithms. In order to tamper with the classification results, the researchers added noise generated from AML into the image data. False classification of image data can have deadly effects. For example an autonomous car with multiple audio, visual and electromagnetic sensors gathers data from the road and surrounding environment. The system is then required to process this data at extremely high speed, in order to make time critical driving decisions. Should this data be tampered with, then autonomous driving decisions will become risk laden and insecure (Nyholm and Smids, 2016). From a Defence Industry perspective; the argument that Lethal Autonomous Weapon Systems (LAWS), known as 'killer robots' could lead to more effective and less lethal warfare (Krishnan, 2009) is severely undermined when we consider that these robots could be targeted by AML to perform in undesirable ways.

AML techniques have the potential to bypass conventional legal and ethical ways of governing innovation as they function in a way that we may not be aware of, or able to see. Powerful states, large corporations and academic institutions with the intent, resources and/or societal interest are investing heavily in AML research and development. The nature of the phenomena means researching and developing offensive and defensive AML capabilities is necessary. Currently, AML is not governed by international treaties, code of ethics or, in the case of nuclear weapons, any existential fear of mutually assured destruction. Instead, AML displays its power potential when in the hands of anyone who has an interest and motivation to apply it. For an entrepreneur, or an adversary targeting an organisation that may be applying ML in their enterprise to boost productivity and performance, AML is a powerful asset or liability of AI that cannot be overlooked. The knowledge and resources needed to apply AML are readily available and require little skill acquisition to apply and release into the wild (Parkin, 2019).

AML can have transformative potential for AI. However the potential hostile applications of AML can have catastrophic and fateful consequences. These range from manipulating audio, visual, textual content to 'killer robots' turning on their 'masters', or worse still on innocent civilians. Due to the novelty of this technology as well as its application and proliferation, there is a need for expert developers and entrepreneurs to think holistically and collaborate concerning the problem space. This requires cognitive agility founded on a willingness to engage in a metacognitive learning process. This develops understanding of the wider domain context, and self-governance to ensure maladaptive psychological traits do not increase blind-spots and reinforce existing bias. Without this, communication and collaboration efforts will reveal the cognitive vulnerabilities that the AML is perfectly suited to exploit.

Cognitive Demands from a Entrepreneur Perspective

As established above, an effective application of AI technology in an entrepreneurial context does require human decisions about the AI's role and a shared mental model about the demands, potentials and limits of the AI itself. Beyond that and rarely discussed, cognitive-psychological demands on the entrepreneur co-determine whether AI's potential is used and the effects its application reveals. In the following, the user perspective will be taken and the demands for cognitive expertise required by users of AI will be discussed.

AI solutions are of particular interest where human cognitive capacity is exceeded when the amount and/or the complexity of information exceeds human processing capacity and/or speed. This makes AI solutions particularly relevant in entrepreneurial situations that can at times be characterized as Volatile, Uncertain, Complex and Ambiguous ("VUCA"; Bennis and Nanus, 1985). From an entrepreneurial point of view, AI assisting in decision-making may from time to time come into conflict with experience-based and therefore intuition-based entrepreneurial decision-making. An AI producing recommendations, guidance or decisions that are in conflict with an entrepreneurs' situational awareness, resulting expectations and intuitively convincing conclusions, provokes potential conflicts with the possibility of inconsistent human behavior due to ongoing re-definitions of AI's role, and a deteriorating acceptance of AI use. To avoid implementation failures, various aspects of entrepreneurial governance impact the extent and the effect of the use of AI in entrepreneurial decisions need to be clarified at an early stage (Burgess, 2017). These clarifications include a) the decision over purposes for which AI facilities will be implemented (i.e., the definition of the 'search room'); b) the decision over the extent; c) how the interpretation, sensemaking and conclusion drawing happens (under whose involvement and in which roles and interdisciplinary aspects); d) the perceived relevance/trustworthiness and resulting impact on actual decisions the human entrepreneurial side is willing to accept contrary to conflicting beliefs or expectations. These clarifications will to a considerable extent be determined by the entrepreneur's personality. Interindividual differences in decision-making styles, openness and trust will be decisive for the effect available AI technology will have - and in how far it will penetrate all layers of entrepreneurial decision-making.

Following the initial clarifications concerning the area and degree of AI implementation, and a consensus regarding the role of AI results, their trustworthiness and the conditions under which they will be internally accepted and followed, there remains in some entrepreneurial contexts, a need for the outward communication of AI-based decisions to ensure public acceptance amongst non-operative stakeholders (shareholders, customers, cooperation partners, employees, unions, etc.). Where AI-decision consequences affect economic or other circumstances of those affected by entrepreneurial decisions - employees or customers or business partners - perceived acceptance in these groups will determine further action regarding communication, justification and consequently future AI implementation.

The entrepreneurial a priori decision as to when and to what extent AI benefits are harvested, requires from the entrepreneur a certain level of insight into his/her own decision-making process, its limits, biases and possibilities. Metacognition is a key element not only for general leadership qualities, but also for successful AI implementation. The term metacognitive awareness describes the ability to be aware of one's own cognitive processes (for example decision-making processes), their fallacies, biases, the elements of intuition, and presently influencing situational and personal factors of short- and long-term character. Higher metacognitive awareness is related to better decision-making (Batha and Carroll, 2007). Metacognitive skills are therefore supportive for the recruitment and implementation of AI-based enrichments of entrepreneurial processes.

In sum, on an individual entrepreneurial perspective level, as users of AI, they have to become 'experts'. The skill-set needed for that purpose includes the ability to judge one's own decision-making limitations; the knowledge about the interrelationship between AI-design decisions made by technical experts and decision-making outcomes (biases) resulting from AI use; the communication skills incorporating differing levels of acceptance by those affected by decisions where communication is required; and a good level of awareness of the influencing factors on one's own interpretation of AI results, and how the presentation of these affects conclusions.

In the VUCA environment where entrepreneurs often act, control is key. Ironically though, the conscious handover of power by entrepreneurs to AI, in for example the ungoverned domain of cyberspace, challenges this control paradigm as it is the AI that is empowered by the autonomy afforded to it by its human 'controller'. What AI brings to innovation performance is an augmentation capability that can trigger, catalyze, and accelerate the development of entrepreneurial actions at a far greater speed than ever before. But the exertion of this power is moderated by the psychological conditions in which the entrepreneur knowingly or unknowingly operates.

Cognitive Demands from a Developer Perspective

The developers' cognitive styles are mismatched to the entrepreneurial needs and this places extra demands on their contributions. Developers need to understand the vision and the outcomes the entrepreneur sets. This may be problematic due to the ambiguous domain the entrepreneur operates in. Developers are reliant on specifics to determine algorithm development, but these specific objectives are lacking in visionary and unknown domains. Therefore the developer must not only have the technical knowledge on how to develop the AI algorithms, they must also understand the cognitive processes of open communication with entrepreneurs, being able to use cognitive task analysis (or the 'Locating' phase of the OLB model) to understand the needs and wanted end outcomes in order to develop a domain understanding, and understand how the final AI product will be perceived, its uses and limitations. Developers are detail focused and this may lead to a loss of holistic understanding that could hinder the process (Lugo et al., 2019). Developers could struggle to understand the ambiguous end results set by the entrepreneur. Thus, the developer, even if more reserved in nature, needs to have an understanding of their biases and tendencies in order to regulate their own behaviour. Similar to what was described earlier in the OLB model, the developer needs the ability to interact with an entrepreneur who may be difficult to understand, and who may have difficulty in understanding the technical design aspects. Developers will also program systems based on their own intuition and preferences. While this may be beneficial in predictable domains, it might be an incorrect strategy in the innovation process. Developers thus need to develop their metacognition through a reflective criticism of their own tendencies and biases, behaviours, and understanding how other people act, in order to be more receptive to the task. Expanding their understanding will allow for a better governance of their domain and adopt more objective approaches in developing intelligent systems in order to help the entrepreneur.

Observing the differing perspectives and the cognitive demands placed on the entrepreneur and developer sets a focus on the need for cognitive skill development. Different professional backgrounds or opposing world-views can create tension, explainability issues, blind-spots, and biases grounded in psychological traits. Unaddressed, these factors can contribute to performance errors due to lack of trust, transparency, interpretability, lack of tolerance or understanding. This is no different in the innovation space of AI (Miller, 2019).

COGNITIVE SKILLS

As the use of AI increases, developers are required to have a broader domain knowledge that includes not only technical aspects of programming AI, but it must include knowledge of cognitive sciences. Recent discussion showed that more than one third of executives identified that AI initiatives are lacking experts and entrepreneurs' understanding of cognitive technologies (aka AI) is poor (Davenport and Ronanki, 2018). While developer-expert and entrepreneur-expert understandings of AI functioning may be different, both groups can understand the cognitive science behind the AI. Developers need to understand how to program algorithms that are based on evidence from cognitive science, while entrepreneurs need to understand how the AI made its decisions so that a final decision can be made. Possessing cognitive agility founded on metacognitive functions enables the reflective capacity to understand how biases, and decision-making can affect optimal performance.

AI needs to assist humans in the decision-making process. However it cannot make the decisions for them (Carter and Nielsen, 2017; Jarrahi, 2018). Given that expertise in AI development is scarce (Davenport and Ronanki 2018), both the developer and the entrepreneur need to develop a common understanding of the application of AI. Developing this shared mental model and expertise in the functioning of AI, will help the process in several ways. When the developers domain cognisance incorporates both the technical requirements and the understanding of the entrepreneurs end goals, this will guide the developers in constructing the intelligent systems with the proper cognitive architectures in the AI, with the proper rules and regulatory processes needed for the AI to function as desired (Laird et al., 2017). Having an expanded domain understanding will then help developers identify factors that can cause the AI to fail through for example bottlenecking, and will enable the AI to be used to augment decision-making for the entrepreneur (Davenport and Ronanki 2018).

As described earlier, both the developer and the entrepreneur need to take the other's perspective if they are to holistically understand the benefits and limitations of the AI as an intelligent system. AI can assist in scaling up plans by managing lower level goals. It can also be integrated into more high level goals. However when it comes to equivocal decision-making, the AI is limited. Equivocal decision-making is performed by the entrepreneur and involves balancing end outcomes of competing and divergent end users or entities (Jarrahi, 2018).

While developers may have confidence in their product, they, alongside the entrepreneurs, need to understand that AI can fail through several factors (Russel et al., 2015). AI can fail in verification by not satisfying the formal properties of the problem it was developed for. System developers usually only have partial knowledge of the domain and may only have partial control of the AI if it is developed to be self-reliant. To help with verification failures, the AI needs to have self-improving systems, but this then requires that the developer has a good understanding of the entrepreneurs domain and vice versa. AI can have validity failures, where it does not meet the requirements or the standard fit it was designed for. This may also be due to the AI generating unwanted connections, specifications or consequences. The developer and entrepreneur domains need to inform each other of these aspects.

An AI system that is more autonomous can have higher long-term costs. AI can fail in its control systems if left alone in two ways. Since the AI is developed with reinforcement learning algorithms, these processes are susceptible to agent manipulation, or the AI corrigible systems can prevent any outside changes from the developer. Therefore humans need to be both in the loop and on the loop. AI needs to be secured by both the developer, for technical aspects, and by the entrepreneur who has an understanding of outside agents interested in the AI’s analyses.

The situations described above emphasize the requirement for metacognitive competencies if key actors are to understand their own behaviour and how it influences behaviours in the others. For example, an entrepreneur needs to have an understanding of how their extroversion can be perceived as threatening by the developer, and how this interaction can lead to under performance. Jointly, both the developer and entrepreneur need to develop domain cognisance that includes knowledge of the others expertise. This will help in calibrating development of the AI and the eventual outcomes. Entrepreneurs need to understand how developers' biases can be incorporated into AI systems, while developers need to understand how entrepreneurs will perceive and use AI outcomes. This involves developing expertise not only within the domain one operates in, but also a level of decision-making expertise of the other’s domain. Increasing the metacognition of both actors, as well as having a complementary shared mental model, will decrease the chances of AI failures (Russell et al., 2015), while building more transparent and interpretable systems that can increase trust and usefulness of the intelligent systems (Miller, 2019).

EXPERTISE

The development of AI as a catalyst for innovation activity is currently dependent upon human psychology. Success is relient on a conflation of interdisciplinary experts designing and applying AI to trigger, accelerate, exploit and invent.

The topic of expertise is central to the discussion of developing human cognitive skills for better performance in AI innovation. In general, conditions for developing expertise are reliant on a deliberate practice approach (see Ericsson et al., 1993), where specific scenario training leads to targeted experience (see Dreyfus and Dreyfus, 1986) in one's domain. In addition to these, there are two further examples of communities of interest in the study of expertise: the idea of learning from previous or similar tasks, and phased skill acquisition (Fitts, 1964). Fitts describes the final phase of skill acquisition is characteristic of automatic behaviour. This view point is challenged by the speculations of Ericsson and Ward (2007) who consider experts actively defer automating skill so as to "maintain conscious control and/or access to underlying representational structures" (Ward et al., 2020). This 'adaptive skills' approach has been the focus of some of the most recent expertise research, most notably adaptive skills have been defined as the *conditio sine qua non* of expertise (Ward et al., 2018).

The expertise needed to prosper in the information-rich twenty-first century have been described as "the ability to reason about complex concepts, explain these concepts to others, and accept challenges to one's ideas" (Resnick et al., 2020, p. 903). When we consider the exponential growth and complexity of the digital universe that we, to varying degrees, interact with everyday of our lives, one finds it hard to challenge the political scientist Joseph Nye when he wrote over a decade ago that the cyber universe is "way beyond anyone's understanding" (Nye, 2010, p. 17). We have created and continue to develop a cyberspace enabled digital universe that outperforms our ability to reason as the expertise of AI and ML take on the task of processing, interpreting and evaluating information. This leaves the human with the task of drawing fluidly and flexibly on the information presented. This requires willingness to change one's mind and behaviour, and is based on a complex set of skills, attitudes and 'reasoning expertise' (Resnick et al., 2020). AI and ML do not currently have these attributes and humans have a tendency to find them hard processes. Consequently, there is a paradoxical evolution where Artificial General Intelligence (AGI) is being developed to take on these cognitively hard tasks. AGI is a highly contentious and extremely innovative field that demands research scrutiny that is beyond the scope of this chapter.

Similar to the cyberspace domain, the rapidly evolving context of AI technologies and their applications makes it impossible for individuals to develop in-depth sustainable expertise (Thomson, 2019). Instead, a commitment to life-long learning is required. In the case of cyber and AI, domains that touch us all, life-long learning applies to everyone who wishes to avoid being exploited by, or unintentionally becoming part of a new attack vector. The committed AI developer and entrepreneur need to exhibit a) strong situational awareness and b) a willingness to conduct continual risk assessments. These, along with the pre-conditions of expertise: practice, training and experience in one's domain can be generalized to the AI domain as they lead to accurate and rapid deployment of attentional and reasoning processes during complex decision making (e.g., Hoffman, 1998; Hoffman, et al., 2013). As a means of defining expertise in AI innovation, these factors may be more appropriate than judging expertise based upon questionnaires, peer identification, or self-selection (Rajivan, et al., 2017).

Keeping pace with technological acceleration in the field of AI development and application is a human factors challenge. How the expertise of the developer is aligned with the entrepreneurs own ideas of application is reliant upon cognitive skills and shaping the technology for their intended outcomes. It is important then that both understand the role critical thinking has in supporting attentional focus on global aspects and specific details. They must appreciate the importance of developing cognitive skills that enable short and long-term perspective taking and having an agile mindset to maintain vigilance without compromising overall performance. Approaching AI with cognitive agility means entrepreneurs innovate whilst applying requisite cognitive skills to govern and regulate their own behaviours, such as specific domain knowledge, reasoning skills, metacognition and critical thinking.

AI: An Interdisciplinary Domain of Expertise

The required cognitive skill-sets that have been identified need to be acquired, trained and maintained if the application of AI is to be successfully sustained and further integrated into aspects and functions of our daily lives.

Expertise from across disciplines apply and benefit from AI. Industry leaders see the opportunity to transform their enterprise with modern technology will need to transform their workforce. For AI to work for innovation there is a skill gap and a shortage of interdisciplinary expertise where people with specific technical skill and domain knowledge meet experts with insight in ethics, autonomy, understanding of the legal and regulatory terrain, as well as how to: "embed trustworthiness, dependability, safety and privacy through the development" of AI (Zillner et al., 2020). Innovation in AI is about leaders, developers and end-users from across disciplines combining their skills and capacities in order to ensure AI achieves its goals. The challenge of bridging between the different fields and types of expertise may present one of the greatest challenges to the meaningful and successful input and output functionality of AI. Methods to establish productive partnerships should aim to align organizational speed and bureaucratic requirements. This way, any differences between the objectives of developers and entrepreneurs are minimized when primary objectives, cultural differences, psychological profiles can be integrated, aligned and negotiated.

To achieve such defining standards requires educational techniques that are focused on helping people acquire, train and maintain metacognitive and adaptive expertise.

To maximise the positive opportunities for the described actors and the interdisciplinary nature of AI as a tool for the considered application of AI, continuous education is necessary. Slow education can be informal and supports the contextualisation of knowledge and skills so they manifest in the form of improved praxis (Klein, 1998; Ward et al., 2013).

Constructivist pedagogical approaches are capable of supporting Human AI Regulatory Skills (HAIRS) as well as accelerating learning and improving performance by building deeper knowledge grounded in the aforementioned metacognitive strategies such as reflective practice and self-regulation (Kember et al., 2000; Panadero, 2017; Piaget, 1964; Zimmerman, 2000). A complementary approach to Acquiring, Training and Maintaining (ATM) the required skill-sets for expertise in the use of AI can be achieved through a constructivist 'slow' approach to learning. The principles of Slow approaches being 'adaptive' and 'non-standards-based' align with entrepreneurial practices and values such as 'idea transformation' and 'achievement orientation' based on actions (Kets de Vries, 1985). Centered on the learner (see Weimer, 2002) Slow education applauds self-expression, individual interests and innovation capacities (Holt, 2002). By facilitating increased situational self-efficacy and empowerment learners are motivated by engaging in the process of reflective practice and critical thinking (Bandura, 1997). This leads to learners: "...displaying richer intertextual connections [...] and meanings..." (Jenson, 2016, p. 35). This addition to ATM AI skill-sets can support bridging the fields of expertise between the developer, entrepreneur and AI triad. The education goals are then orientated around cognitive engineering processes that enable greater vigilance around what we should actually be doing with AI to improve the overall human-AI system performance.

The adaptability of Slow pedagogies means educators and learners can maintain control of the process and approach depending upon their needs and preferences. Introducing complementary pedagogies such as a) Dialogue Pedagogy for acquiring knowledge through communicative interactions (see Freire, 1970; Wells, 1999), b) Cooperative Learning for positive interdependence and individual accountability (see Cooper, 1990), and c) Critical Pedagogy for awakening of the critical consciousness (see Giroux, 1989) that all fall within the Slow frame, means techniques are introduced through dialogue rather than a imposing a one-size-fits-all approach. Replacing the direct transmission of knowledge with collaborative and individual procedures promoting critical thinking and reflection (Shaw et al., 2013; Schon, 1987) can lead to improved expertise in the innovative application of AI.

Slow techniques can create and deepen knowledge as they have the capability to aid orientation and learner understanding (Hannafin, 2010). When actors are expected to monitor and control their learning (Zimmerman, 2001) then they will engage in a variety of cognitive processes that have the potential to secure expanded domain understanding and self-governance. For example, being cognizant of exercising metacognitive skills builds authentic real-world knowledge through the process of assessment, evaluation, planning, application, monitoring, and reflection (Ambrose et al., 2010). This can be of particular use when dealing with the human-user and technological challenges of AI. When critically considered, any application of AI has (should have) legal and ethical limitations/frames, strategic guidelines, rigorous testing before deployment, transparency and trust mechanisms, and continuous risk analysis based on planned uses, envisioned and actual outcomes. Control in all these areas requires deep knowledge of the desired operational effects and potential negative impacts and consequences, should the AI not perform the way human users expect it to. Slow approaches have the pedagogic potential to develop the essential interdisciplinary cognitive skills to responsibly enable AI.

CONCLUSION

The application of AI in an innovation context is an interdisciplinary activity that requires honed cognitive skills among collaborating actors. Where divergent psychological and technological profiles intersect for the purpose of utilising an emerging and disruptive technology, there is a pressing need to reduce uncertainty.

Communication errors do occur, but can be avoided. Adversarial actions can lead to bad data in machine learning algorithms, but can be reduced if actors are aware of cognitive blind-spots and bias. Ensuring the human is the AI enabler means applying methods that support better cognitive control and understanding. As the nature of work in today's society continues to become increasingly cognitive as a result of technological advancement, this should act as a catalyst for developers and entrepreneurs to acquire the appropriate 'whole domain' skills and act with cognitive agility. AI is slated to solve the greatest challenges we face from environmental sustainability, energy, food and water security, and improving health and quality of life. As the core driver of innovation, productivity and economic growth, AI has to remain human-centric. Human cognitive skill development is therefore instrumental to ensure innovation responsibly utilizes the full potential of AI.

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