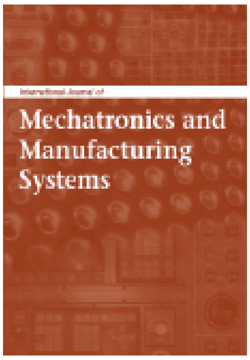

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Integration of human factors, cognitive ergonomics, and artificial intelligence in the human-machine interface for additive manufacturing

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Abstract: As additive manufacturing transitions from manufacturing prototypes to rapid manufacturing, more human factors considerations must be assessed and integrated for improved work design. This review paper provides an overview of human-machine integration for human factors, cognitive ergonomics, and artificial intelligence to improve the performance output of the additive manufacturing process. In addition, case studies are shared to provide integration concepts for artificially intelligent systems. It is anticipated that the contents of this review paper will pave the path for further research into the integration of human factors and cognitive ergonomics for artificial intelligence in additive manufacturing.

Keywords: additive manufacturing; artificial intelligence; cognitive ergonomics; design-evaluate-justify-integrate (DEJI) model; human-machine integration; mental workload; work design.

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1 Introduction

Much has been stated and written about the current and future potential of additive manufacturing. However, one area that has not been adequately addressed is Human Factors and Ergonomics in additive manufacturing concerning promoting better system performance. As additive manufacturing transitions from a technology of manufacturing prototypes to rapid manufacturing, more human factors considerations must be assessed and integrated for improved work design. This paper provides an overview of human-machine integration for human factors, cognitive ergonomics, and artificial intelligence to improve the performance output in the additive manufacturing process.

2 Background

2.1 Additive manufacturing

Additive manufacturing (AM) is a fabrication process that deposits, cures, or consolidates material layer upon layer to create a product (Horn and Harrison, 2012). The product formed is based on a three-dimensional (3D) model made from computer-aided-design (CAD) software like SolidWorks. When additive manufacturing first originated in the 1980s, its primary use was for rapid prototyping products due to reducing both time and cost compared to other traditional manufacturing methods such as milling and drilling

(Gardan, 2016). Today, additive manufacturing's primary use remains for rapid prototyping. Although additive manufacturing has not become more common in the manufacturing environment outside of prototyping due to the technology remaining expensive and unable to mass-produce (Bailey and Bosworth, 2014), the industry is slowly growing (Bikas et al., 2016). General Electric is one company that has led the growth of metal additive manufacturing with its recent use and development of 3D printing for components used in its aircraft engines (Sand, 2019). The success of General Electric's use of additive manufacturing could lead to lowered cost and shortened lead times for them as a company due to the consolidation of manufacturing their components (Sand, 2019), but this could be due to the small batch size of their engines compared to other industries. Although more research is necessary, there are known environmental, ecological, and design benefits with a potential for even more depending on the development of additive manufacturing technologies.

Some of the studied ecological benefits of using additive manufacturing are less raw material needed for production, which leads to a reduction in the weight of transported products and wasteful manufacturing processes, along with the declining need for centralised locations in part manufacturing (Peng et al., 2018). Other potential ecological benefits exist for additive manufacturing such as limited material waste, a recyclable material, and higher energy efficiency, but these benefits are dependent on the design of the product, the material of the product, the amount of excess material used for supporting the part during printing, and the number of products being produced (Rejeski et al., 2018). In terms of economic benefits, the foremost economic interests coincide with additive manufacturing's primary function of rapid prototyping with reduced development costs and material waste during prototyping compared to the traditional subtractive manufacturing processes (Bailey and Bosworth, 2014). The other prospective cost savings that come with additive manufacturing processes have similar variability to environmental benefits with factors such as build failure rates or incorrect fabrication of the product (Baumers et al., 2017). The major advantage of using additive manufacturing is the ease of design and production of models in short product cycles (Horn and Harrison, 2012).

With the direct use of a three-dimensional CAD model to produce a product, additive manufacturing can create a single component that has intricacies that other manufacturing processes cannot replicate. The ability to compose a complex component allows the designer to create a model with sophisticated structures instead of designing for manufacturability and creating a series of pieces requiring final assembly (Mantyjarvi et al., 2018). This freedom of design provided with additive manufacturing allows engineers to design products with higher performance for numerous applications, such as modular weaponry for military use (Schrand, 2016) or aeroplane blades made of high-performance alloys (Horn and Harrison, 2012). Though additive manufacturing has clear and significant advantages for manufacturers beyond rapid prototyping, there are disadvantages to additive manufacturing that have prevented additive manufacturing from growing into a more prominent role in the manufacturing environment.

The significant reasons why additive manufacturing has not become commonplace in the manufacturing environment outside of rapid prototyping is due to its inability to match the throughput, quality, quantity, and product consistency of traditional manufacturing processes that comes at a manageable cost for mass production (Horn and Harrison, 2012). Additive manufacturing has grown with the development of multiple fabrication processes in laser-based processes, extrusion-based processes, material jetting processes, adhesive- based processes, and electron beam processes as well as expanded availability of metals and plastics for producing parts. However, machining is still needed for post-processing of the 3D printing for removing the excess material for the part. Each of these process types has favourable applications compared to the others, but all create parts layer by layer using a CAD model (Bikas et al., 2016). But until all these technologies for additive manufacturing become more reliable and less expensive, it will remain in its current role in rapid prototyping. However, as the additive manufacturing technologies advance to produce at rapid manufacturing rates, the human-in-the-loop must be considered and the use of artificial intelligence. This paper will review and leverage published literature regarding human factors and cognitive assessment methods to evaluate operator performance and the human-system design in additive manufacturing tasks and workstation functions.

2.2 Cognitive ergonomics

In general, ergonomics is the study of human work that seeks to improve the safety, comfort, and production of humans (Venda et al., 2000). Since its origination, ergonomics has been a topic for numerous pieces of research to enhance the work of humans in a variety of work environments. Research in ergonomics was solely on physical ergonomics during its initial stages of development. This research led to the application of physical ergonomic standards in most working environments, thanks to the creation of the Occupational Safety and Health Administration (OSHA). With the growth of technology came a new and more relevant field of ergonomics for today's work environments: cognitive ergonomics.

Cognitive ergonomics analyses human work from a mental work perspective and like physical ergonomics, seeks to improve humans' work and productivity (Venda et al., 2000). The mental work perspective is an essential aspect of designing and evaluating occupational tasks because the interaction between an operator and an assigned task is critical. Mental work measures provide awareness of where increased task demands could negatively impact human performance (Bommer and Fendley, 2018).

Two significant aspects of cognitive ergonomics are people perceive processed information through sight, sound, or feel and how people make decisions based on this information (Macleod, 2004). The use of cognitive ergonomics is seen every day from how a light switch is designed and mounted vertically on a wall (Macleod, 2004) or how a door unlocks when the door handle is pushed down on instead of up. Subtle changes such as a door handle and light switch are designed to be easily used and follow perception and decision making that humans are accustomed too. Cognitive ergonomics are also applied to high-stress environments such as an airplane's cockpit, its endless number of buttons and switches being designed and placed for a typical pilot's decision-making (Macleod, 2004). Cognitive ergonomics is used for developing a product comfortably for humans and increasing the performance of a product and its user and the safety of the person producing the product.

As stated previously, one of the central focuses of ergonomics is to increase the safety of humans (Venda et al., 2000), which is vital in hazardous environments such as manufacturing or construction. An example of designing for safety in the design of construction safety signs (Chen et al., 2018). In a study done on the construction safety signs, results showed that if the sign was the colour red, the signs were easier to identify with shorter response time compared to other coloured signs (Chen et al., 2018). Other safety precautions follow this knowledge of red being an ideal colour, such as how a computer numerical control (CNC) has a red emergency button that can completely shut down a machine. A CNC also can produce a noise like a siren to increase the attention of an operator to alert that operator that something is incorrect with the setup or operation of the machine and not to precede with the operation (Wei et al., 2018). Lastly, cognitive ergonomics is used to increase human production (Venda et al., 2000) such as presenting information in appropriate detail (Macleod, 2004) when working on a computer interface to avoid mentally overloading the human operating the computer interface. Cognitive ergonomics' central focuses revolve around the idea of cognitive load and avoiding mental overload and under-stimulation for humans.

Cognitive load theory (CLT) defines human limitations in processing information in working memory from three distinct loads: intrinsic, extraneous, and germane (Galy and Melan, 2015). First, intrinsic cognitive load is the quantity of material required for processing and the difficulty of the material being processed (Galy and Melan, 2015). Secondly, extraneous cognitive load is the elements of one's learning environment that can negatively or positively affect one's workload (Galy and Melan, 2015). Lastly, the germane mental workload is the load that is generated by the applications of problem-solving techniques (Galy and Melan, 2015). All three of these loads are factored into both types of memory: working memory and long-term memory (Kalyuga, 2011). Working memory is temporary memory that one contemplates based on the information they perceive (Wickens and Lee, 2004) while long-term memory is information that can be retrieved from the past, whether it be minutes later to years later (Wickens and Lee, 2004). Understanding these different types of workload and memory provides insight into the various cognitive abilities required for an operator. Furthermore, knowledge of these workloads as well as the multiple resources that factor into one's mental workload allows one to measure the cognitive workload of an operator and acquire a more holistic understanding of their workload and whether one's performance is a result of their task demands (Bommer and Fendley, 2018).

The Multiple Resource Theory (MRT) assesses task demand by considering the resources that factor into the workload of humans and a human's ability to perform in high-workload environments (Wickens, 2002). The five resources of the human mind that factor into a human's performance are visual processing, auditory processing, cognitive processing, speech, and motor (Bommer and Fendley, 2018). With these five resources in mind, the Multiple Resource Theory analyses three specific components within a compilation of the five resources: task demands, availability of resources, and resource overlap (Bommer and Fendley, 2018). By analysing these three components, the evaluation of an operator will be holistic by completely breaking down all the elements to one's task performance. This analysis will also allow one to predict an operator's performance and their ability to complete their given task or tasks (Bommer and Fendley, 2018). The CLT provides insight into the distinct three mental workloads. The Multiple Resource Theory breaks down a human's performance by analysing the five resources that factor into mental workload. These two theories can be applied by selecting an appropriate resource or resources to measure a human's performance and the distinct mental workload needed to complete the operator's given tasks.

2.3 Computational methods

For measuring mental or cognitive workload, there are three types of measures: physiological, subjective, and performance. Physiological measures are measures of the body's physical responses that range from eye fixation rate to the pitch of one's voice (Badiru and Bommer, 2017). These physiological measures include measuring the resources outlined in the Multiple Resource Theory by using bodily activities of the following: cardiac, brain, respiratory, speech, and eye (Badiru and Bommer, 2017).

The cardiac measures for mental workload include heart rate (HR), heart rate variability (HRV), and absolute interbeat intervals (Grassmann et al., 2017). Some of the physiological measures of the brain can be measured using an electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG), or an electromyogram (EMG) (Zhang et al., 2017). Respiratory measures for mental workload include the respiratory rate, airflow, and volume, along with respiratory gas analysis (Charles and Nixon, 2019). Speech measures used for measuring mental workload include the pitch, rate, and loudness of speech (Badiru and Bommer, 2017). Lastly, the eye measures used in calculating mental workload include pupil dilation, blink rate, fixation rate, saccadic rate, and pupil diameter (Yan et al., 2019).

Generally, physiological measures have been used in measuring mental workload due to the measurements providing accurate and objective data (Zhao et al., 2018). Physiological measures are also known for having better performances in measurement facets such as sensitivity, diagnostic ability, and non-intrusiveness when comparing it to subjective measures (Zhao et al., 2018). Subjective measures provide a different dynamic to measuring one's cognitive workload that physiological measures do not offer with the measure being based on the operator's perception (Badiru and Bommer, 2017).

Subjective measures are easier to administer and analyse compared to physiological measures but are administered after the task or tasks have been completed, which can affect the reliability of the results if the task or tasks are extensive (Longo, 2015). Subjective mental workload measures include the Workload Profile (WP), Cooper-Harper scales, Bedford scale, subjective workload assessment technique (SWAT), subjective workload dominance technique (SWORD), and the National Aeronautics and Space Administration Task Load (NASA-TLX) (Badiru and Bommer, 2017).

Workload Profile collects data on demands of the task which includes perceptual processing, response selection execution, spatial processing, verbal processing, visual processing, auditory processing, manual output, and speech output using a rating system imposed on all of their tasks with these dimensions being analysed (Badiru and Bommer, 2017). Like the Workload Profile, Cooper- Harper scales use a rating system that is filled out by operators after the task is completed but can use a decision tree in conjunction with the rating system to analyse the workload of an operator (Moorhouse, 1990). The Bedford workload scale uses a 10-point rating system assigned based on the mental workload of the operator (Wang et al., 2013). For example, ratings 1 to 3 indicate a low workload and the operator has spare mental capacity doing these tasks, while a task with a rating of 10 indicates there is no spare capacity and no available attention that can be permitted to be used on other tasks (Wang et al., 2013).

The subjective workload assessment technique (SWAT) is a subjective questionnaire type analysis that looks at three dimensions: time load, mental effort load, and psychological stress load (Rubio et al., 2004). These three dimensions are then rated on a three-level scale: low (1), medium (2), and high (3) that determines the mental workload of an operator (Rubio et al., 2004). The next step of the SWAT analysis is having an operator rank all 27 possible combinations of the three dimensions and three levels in their perception of increasing workload (Rubio et al., 2004). Following the operator ranking all possible combinations, conjoint scaling procedures are followed to create a single rating scale with interval properties (Rubio et al., 2004). Lastly, actual ratings of workload for given tasks are completed and converted into a numeric score between 0 and 100 using the interval scale (Rubio et al., 2004). The next subjective measure for mental workload that will be covered is the subjective workload dominance method.

The subjective workload dominance (SWORD) measures workload using a series of relative judgements that compares the workload of various task conditions (Vidulich et al., 1991). SWORD follows three distinct steps: collecting raw judgement data, constructing the judgement matrices, and calculating SWORD ratings (Vidulich et al., 1991). In collecting raw judgement data, the rater is given the rating sheet that lists all possible paired comparison of tasks after completing all tasks (Vidulich et al., 1991). This rating sheet has one task on the left side of the evaluation and the other on the right, and the rater has to compare the levels of workload for both of the tasks and determine which task has a higher workload or workload dominant and how dominant it is (Vidulich et al., 1991). The rater does this for all of his tasks before constructing the judgement matrices to compare task difficulty (Vidulich et al., 1991). The rater marks the judgement matrices based off of which task was the dominant (Vidulich et al., 1991). If the left-side task was more dominant, the rater would use a 2 to 9 scale depending on how dominant the left-side task is compared to the right-side task with two being the least dominant and nine the most dominant (Vidulich et al., 1991). If the right-side task was more dominant, the rater would use the 1⁄2 to 1⁄9 with 1⁄2 being the least dominant and 1/9 being the most dominant (Vidulich et al., 1991). The SWORD rating for each task is then calculated by using the geometric mean for each row of the matrix and normalising the means (Vidulich et al., 1991). The final subjective measurement method for mental workload covered will be NASA-TLX.

Lastly, NASA-TLX has operators rate the mental demand, physical demand, temporal demand, overall performance, effort, and frustration of their tasks in a questionnaire format following the completion of all tasks (Alaimo et al., 2018). The first step to obtaining the rating for each dimension is assigning a score on twenty-step bipolar scales for each dimension (Rubio et al., 2004). A score from 0 to 100 is received on each scale, and then using a paired comparison between all six dimensions is completed to consolidate the six individual ratings into a single score (Rubio et al., 2004). The pairwise comparison requires an operator to pick the dimension that is most relevant to workload out of all the pairs of the six dimensions (Rubio et al., 2004). The weighting of a dimension scale for each task is determined by the number of times the dimension is picked as the most relevant (Rubio et al., 2004). Finally, the workload score is computed by multiplying the weight by the individual dimension scale score, summing across all scales, and dividing by 15, which is the total number of paired comparisons (Rubio et al., 2004). Performance measures are discussed in the next section.

The first thing to note with performance measures for mental workload is that it assumes that increased task difficulty leads to an increase in task demand (Rubio et al., 2004). To meet this assumption, measuring mental workload based on performance requires the use of two types of measures: primary task and secondary task (Longo, 2015). Primary task measures are used to indicate performance, while secondary task measures are used to calculate one's spare attentional capacity along 9 2 with short periods of workload (Longo, 2015).

A performance measure for mental workload is centred around human error probabilities (HEPs), which are calculated by taking the number of observed errors and dividing it by the number of possibilities for an error (Badiru and Bommer, 2017). There are plenty of analyses used for forecasting HEP, such as the Technique for Human Error Rate Prediction (THERP), and Cognitive Reliability and Error Analysis Method (CREAM) (Liang et al., 2010).

For THERP, the overall HEP is calculated by completing a task analysis that is then converted into a tree diagram that displays all the human errors possible for each task (Shirley et al., 2015). HEPs are then subjectively estimated for each possible error, and the overall HEP is computed using all the HEPs from each task (Shirley et al., 2015). The CREAM method is a human error classification method system that divides human errors into eight error modes and three headings of influence factors that gives a framework for evaluating human error (Liao et al., 2016). Like THERP, CREAM forecasts HEPs subjectively through the opinions of experts (Liao et al., 2016). The use of performance measures does allow for a detailed analysis of the resources competing between one another in tasks (Longo, 2015) but lacks the objectivity of physiological measures and input of operators that subjective measures include.

Cognitive ergonomics have made significant progress from its origination to now with several theories being developed and applied to a multitude of studies and experiments. The development of the theories such as the CLT and Multiple Resource Theory which have helped in distinguishing the various mental workloads that humans deal with, the resources that go into receiving and retaining information, and how to measure mental workload overall. Subjective, physiological, and performance measures have been developed and used in a variety of work environments to analyse human performance. The results of these measurements have been analysed and tested to produce modifications to tasks, workstations, and/or product designs to adapt to human perception (Macleod, 2004) and potentially increasing productivity and/or safety of the human (Chen et al., 2018).

3 Human considerations in additive manufacturing

Human considerations in additive manufacturing stem from the three goals of human factors: increasing safety, enhancing performance, and increasing user satisfaction (Wickens and Lee, 2004). Of these three factors, the most prominent issue with additive manufacturing currently is the safety hazards that could damage a human's health and, eventually, the environment (Bours et al., 2017). The three main safety hazards for humans is the exposure of toxic chemicals throughout the manufacturing process, the harmful emissions produced in some of the processes, and potential static causing hazardous materials to react (Bours et al., 2017). For enhancing the performance of additive manufacturing, there is definite room for growth in the performance of additive manufacturing systems in their throughput, quality, and product consistency of the 3D printer (Horn and Harrison, 2012) as well as the energy consumed in additive manufacturing's unit processes (Kellens et al., 2017).

In terms of the human performance in these systems, training and gaining experience with 3D modelling and the process of printing 3D models on a 3D printer safely and properly are the two primary enhancement methods for a human's performance in additive manufacturing (Shelton, 2019). Improvements to the user's interface for the computer used to create the 3D models, and the interface for the 3D printers along with how the additive manufacturing process is managed and analysed are improvements to the technology that can increase human performance. The idea of incorporating more artificial intelligence in the process should also increase human performance in additive manufacturing. User satisfaction can be increased mostly through making the user interfaces on three- dimensional software like SolidWorks or Autodesk Inventor and the 3D printer more user-friendly by providing the right amount of feedback and simple design (Lee et al., 2010). The advantages and disadvantages slightly differ on the additive manufacturing process used whether that is selective laser melting, selective laser sintering, fused deposition modelling, or stereolithography (Bikas et al., 2016), but the safety potential benefits and concerns for each of these processes are similar. Some of the potential safety benefits for additive manufacturing is that there is less material, produce less waste, and the process is more self-contained compared to the conventional manufacturing processes (Rejeski et al., 2018). Unlike popular manufacturing methods, additive manufacturing methods present similar safety concerns from the hazardous materials used to managing the harmful emissions produced during the manufacturing processes (Rejeski, et al., 2018).

A major difference between additive manufacturing and modern-day manufacturing processes is the materials used which present different health hazards such as higher toxicity in materials used, an overabundance of static produced in the process that could potentially cause a reaction between materials used in the process (Shelton, 2019), and the different emissions that are released (Rejeski et al., 2018). The toxicity hazard is minimised by handling materials with no direct contact, such as setting and cleaning up the 3D printer through gloves that are attached to the glass window (Shelton, 2019). Oxygen is consistently monitored in the room to assure there are no harmful toxins that can be inhaled and in other processes such as the filtration process where excess powder filters out any toxic materials so the excess powder can be reused (Shelton, 2019). If the percentage of oxygen in the room goes below a certain threshold, anyone in the room is alarmed to evacuate immediately (Shelton, 2019). If the percentage of oxygen goes below an operator set level during the filtration process, the machine automatically shuts off to prevent any exposure to toxic particles (Shelton, 2019).

For reducing the chance of a reaction, static is reduced with the use full-body suits that are fire retardant and electrostatic discharge (ESD) shoes during the transfer of the metal powder along with an ESD floor (Shelton, 2019). Another form of personal protection equipment (PPE) used during the transfer of the metal powder is a positive pressure helmet that breaks down toxic particles and pushes them out of the helmet to prevent the particles from being inhaled (Shelton, 2019). Another safety hazard that additive manufacturing has is the harmful emissions that are produced in the 3D printing process. Research has been done regarding reducing emissions in the additive manufacturing process, and one tactic that has been found to reduce the emissions is to use a high-efficiency filter in an enclosed, well- ventilated indoor environment that could help alleviate this safety concern (Kwon et al., 2017).

The other safety and health concerns with additive manufacturing reside in the 3D modelling portion of additive manufacturing.

The safety concerns that come with 3D modelling are like that of a typical office worker such as the potential for computer vision syndrome (CVS) due to the extended use of a computer (Teo et al., 2019) or carpal tunnel syndrome (CTS) due to the use of keyboard or mouse that lack in ergonomic design (Liu et al., 2016). The health concerns with excess computer use have been studied extensively with well-known mitigation strategies in place for these. For computer vision syndrome, reduction methods include optimising lighting within the room, the position of your computer, taking breaks throughout the day, using lubricating eye drops, and computer glasses that reduce exposure to blue light (Teo et al., 2019). The use of a pad for both the mouse and keyboard has also proven to provide support for the wrists to improve their posture, thus helping prevent carpal tunnel syndrome (Liu et al., 2016). There are some methods for enhancing the performance of humans in additive manufacturing outside of more training and experience like improving the interface of the 3D printer and increasing the use of artificial intelligence (AI) in additive manufacturing and the artificial intelligence's effectiveness.

Since most of the work for humans in additive manufacturing comes from the time needed to 3D model a part, proper training and experience with 3D modelling are the primary ways to enhance the performance of a human. The 3D modelling software's interface, as well as the interface of the additive manufacturing machine or 3D printer, is another way the performance of a human can be enhanced, which can also lead to higher user satisfaction with the software. Using cognitive ergonomic techniques and guidelines to design both user interfaces can lead to potential rises in performance and satisfaction, such as consistent dialogue box designs, maximising screen space on the interface, and customisability with the system's interface (Lee et al., 2010). The failure analysis of AM could also use improvement by utilising more effective AI in AM systems to effectively improve human performance.

AI is being utilised in three tasks in additive manufacturing: the computer is able to select the point of contact for the part on the 3D printer's platform, the amount of supportive material needed and the supportive material's placement on the part to print properly and providing images of each layer of the part after the part has been printed (Shelton, 2019). These three uses of AI in AM have not been particularly effective with operators choosing a better point of contact for the part and operators choosing the amount of support material needed and its placement which is typically less wasteful than the computer's support material suggested along with saving time by reducing the time needed to remove the excess material (Shelton, 2019). The images provided for each layer of the part does allow failure analysis post-process but does not monitor the part during the printing process (Shelton, 2019).

The failure analysis is also a tedious process with the vast number of images that are produced and organised in chronological order of layer printed need to be analysed when a failure occurs (Shelton, 2019). To reduce the number of failures and re-printing of parts, a potential new application of AI in additive manufacturing could be used to analyse if a part can be successfully printed instead of having a human operator take a significant amount of time to assess the build and revise it if needed (Shelton, 2019). Instituting this technology would remove a stressful task for the operator and reduce the mental workload for the operator while potentially increasing the performance of the operator if the AI is effective in determining if a build is printable or not (Shelton, 2019). The current AI technologies in additive manufacturing need to be improved to meet the performance of a human to reduce the workload on the human in strenuous tasks such as 3D build assessment.

4 Artificial intelligence case studies

Artificial intelligence (AI) was first thought of by the philosopher Thomas Hobbes in the 1650s with his philosophy on thinking consisting of symbolic operations that can be deduced mathematically (Badiru and Cheung, 2002). The development of the computer and its capabilities led to machine intelligence growing and methods for how this intelligence can be evaluated with tests such as the Turing test (Badiru and Cheung, 2002). The Turing test tasks a human interrogator with asking questions to two parties (a male and female for the first portion of the test and a computer and human for the second portion of the test) through a computer with both parties responding through a separate computer in a different location (Badiru and Cheung, 2002). For both portions of the test, the human interrogator must interpret the responses of the two parties to distinguish which responses are coming from which party with one party responding truthfully to the human interrogator's questions while the other party is attempting to fool the human interrogator (Badiru and Cheung, 2002). The results of the Turing test should indicate whether the computer shows signs of intelligence. If the human interrogator's success rate in distinguishing between the two parties is lower for the computer and the human portion compared to the male and female portion, the computer is considered to be intelligent (Badiru and Cheung, 2002). The intelligence of computers and its programming only continued to grow, which eventually lead to the birth of the term 'artificial intelligence' by John McCarthy in 1956 (Badiru and Cheung, 2002).

After its origination, artificial intelligence began to rapidly grow with the invention of the general problem solver (GPS), LISP (list processing), the computer programming language with great memory organisation and control structure, neural networks, and modern- day expert systems (Badiru and Cheung, 2002).

Herbert Shaw, Allen Newell, and Cliff Shaw introduced GPS, a system that uses means-end analysis to complete tasks such as solve theorems or play chess (Badiru and Cheung, 2002). Around the same time, John McCarthy developed LISP, a new computer programming language that organised its memory with interconnections between memory groups and then controlled its program by starting with a goal and determining the requirements for achieving that goal (Badiru and Cheung, 2002). A neural network is a network where all neurons in a layer are connected to all the neurons in the following layer (Bazrafkan and Corcoran, 2018). Data travels through these layers sequentially to eventually provide an interpretation of one feature of the input data structure (Bazrafkan and Corcoran, 2018). Lastly, expert systems that can mimic a human expert's knowledge and reasoning as well as draw interfaces that normal computer programs cannot (Pandit, 1994). These technologies have continued to develop since their inceptions and become a more integrated society.

Today, AI is changing humans' lives by increasing automation in both our personal and work environments (Calp, 2019). AI has affected numerous work environments from hospitals to manufacturing plants with its ability to assist problems involving issues such as classification or optimisation (Calp, 2019). The algorithms and mathematical models that are the basis for AI have led it solving highly advanced optimisation problems whether the optimisation is continuous or static (Calp, 2019). The use of mechanisms such as random walk, swarm intelligence, algorithmic flow, and heuristic and meta-heuristic can be used to solve these optimisation problems (Calp, 2019).

Artificial intelligence has started being used in additive manufacturing for a variety of purposes that have been well-documented and researched. The use of cognitive ergonomics can assist decision-making on where to deploy AI technologies to effectively support the human operator. Table 1 outlines different forms of artificial intelligence that are being researched or used in additive manufacturing.

Table 1 Artificial intelligent technologies in additive manufacturing

AI Technology	*Task utilisation*	*Citation*
Augmented reality (AR)	Design assessment, real-time monitoring	Malik et al. (2019)
Bayesian networks (BN)	Failure diagnosis	Bacha et al. (2019)
Convolutional neural network (CNN)	Data acquisition, data processing, generating patches/labels, image segmentation	Minnema et al. (2018)
Ensemble-based multi- gene genetic programming (EN-MGGP)	Prediction of surface roughness and waviness	Garg et al. (2018)
Evolutionary algorithms (EAs)	Solving a variety of optimisation problems (e.g., machine set up and process planning)	Simon (2013) and Leirmo and Martinsen (2019)
Graphics processing unit (GPU)	Manipulation of computer graphics, image processing, processing big data	Ongsulee (2017)
Machine learning (ML)	Image processing, text classification, speech recognition	Gardner et al. (2019) and Singh et al. (2016)
Predictive analytics	Predictive modelling, data mining, pattern recognition	Ongsulee (2017)

5 Cognitive ergonomics in additive manufacturing

With technological advancements continually being made and implemented in manufacturing, more focus is needed on cognitive ergonomics that is constantly evaluated like physical ergonomics (Bommer, 2017). One of the most significant technological advancements in manufacturing is additive manufacturing with its ability to create a product based on a three- dimensional model made using software such as SolidWorks. Additive manufacturing, like many technology-driven processes, requires more analysis on the cognitive ergonomics compared to traditional manufacturing processes due to its constant use of a computer interface. Some research has been done on the cognitive workload that comes with additive manufacturing from the workload needed for the spatial design in the CAD (Dadi and Goodrum, 2014) to data organisation and analysis in lifecycle management (Muller et al., 2017), but there is a need for more specified research on the cognitive ergonomics in additive manufacturing. This section will cover some of the current studies completed on cognitive ergonomics in additive manufacturing and other studies conducted on cognitive ergonomics applicable to additive manufacturing processes.

The current trend and changes in manufacturing have led to an increased cognitive workload for various process operators due to an emphasis on problem-solving and reasoning skills in manufacturing tasks and processes (Bommer, 2017). This is especially true in additive manufacturing which does not feature many traditional manufacturing processes such as milling and drilling. Instead, most of the work processes in additive manufacturing are done through a human-computer interface, whether on a computer doing the 3D modelling of the product or setting up the 3D printer to print the 3D model part. Of those two human-computer interfaces, the most time-consuming element for the human is the 3D modelling, so understanding the cognitive workload of 3D modelling using CAD software is critical. Therefore, cognitive ergonomics can be applied to increase productivity for the human operator and ease the mental workload for CAD activities.

One study helped frame the workload required in 3D modelling by analysing the cognitive workload needed for interpreting 2D drawings, a 3D CAD interface, and a 3D printed model by having a person looking at all three models of the product in one of six potential sequences (Dadi and Goodrum, 2014). In this study, mental workload was measured using the subjective measurement method, NASA-TLX (Dadi and Goodrum, 2014). Of the three models, the 3D CAD interface had the highest mean for composite workload, mental workload, effort, and frustration, along with the lowest performance compared to the other two. The study also found that more training and experience in CAD helped reduce those workloads and increase performance (Dadi and Goodrum, 2014). Ultimately, this study outlines the need for using cognitive ergonomics when designing CAD software and the need for training to approve the efficiency of humans in additive manufacturing (Dadi and Goodrum, 2014) while other research has provided insight on the cognitive workload that goes into the of lifecycle management in additive manufacturing (Muller et al., 2017).

Additive manufacturing's ability to quickly produce parts is a major benefit, but the short lifecycle that features multiple datasets with different data formats that have been gathered in manufacturing process makes it difficult to interpret the multitude of data points and draw correlations between product behaviour, product design, and process settings based on these data points (Muller et al., 2017). In a study done on the lifecycle design and management of additive manufacturing, a cognitive workload issue was identified and tested in the management of additive manufacturing technology with the organisation of millions of data points and the consolidation of these points into a single format to analyse the 3D printed prototype (Muller et al., 2017). Though this was believed to be an issue for the demonstrator of the AM process, the demonstrator was able to collect a large amount of data and organise it into a singular and easily accessible database (Muller et al., 2017). Even with the demonstrator's ability to organise and consolidate the multitude of data points into a single format, there are questions on whether this is able to translate to an actual manufacturing environment and the security and safety of the data (Muller et al., 2017).

The CAD software systems use the core principles that other human-computer interactions (HCI) use such as easy to learn, easy to remember, and pleasant to use to make humans more proficient in using the software (Muller et al., 2017). There are other factors that affect a human's cognitive ability in an HCI, such as emotions (Liu et al., 2014). A study was conducted on the emotions of a human working on a CAD system to discover if there is a correlation between the human's emotions and associated CAD tasks (Muller et al., 2017). This research provides more insight into the mental workload involved in CAD- based work, such as additive manufacturing and the 3D modelling done in the process (Liu et al., 2014). The study provided a framework of psycho-physiological analysis in engineering task analysis in CAD operation with the results of the study providing insight on how CAD software could be improved for better performance such as a better interface for completing designs on CAD and separate dialogue boxes for requirements and available configurations (Liu et al., 2014). Along with these suggestions for improving CAD software's interface and management of the additive manufacturing lifecycle, the interface for the 3D printer can also be approved to reduce mental workload by using findings from other research on computer-based procedure systems (Lee et al., 2005).

As previously stated, most of the work done in 3D printing of a part involves HCI, whether it is when modelling the 3D part or setting up the 3D printer to print the 3D modelled part. The previous recommendations for the CAD interface can also be applied to the 3D printer interface (Liu et al., 2014) along with other suggestions such as navigation aid and embedded controls (Lee et al., 2005). In one study done on reducing cognitive workload for a computer-based system, it found that embedded controls produce a better performance time for humans and easier to use compared to separated controls but comes at the cost of limited information for operators and harder to develop and maintain (Lee et al., 2005). For designing the 3D printer's interface, using embedded controls when an abundance of information is not needed for an operation and keeping the computer interface simplistic should reduce the setup time and improve the machine and human performance.

6 Human-machine integration

6.1 Design-Evaluate-Justify-Integrate (DEJI) model

The DEJI model (Figure 1) is a systems engineering model of work design, evaluation, justification, and integration (DEJI^{TM}) (Badiru and Bommer, 2017) that encourages the practice of building relevance into a product in the beginning to increase the success of the integration of the system later (Badiru and Racz, 2018). Originally developed for product development, the DEJI model can be applied to numerous types of programs due to every program going through the four stages of the DEJI model: design, evaluation, justification, and integration (Badiru, 2012). Some of the applications that the DEJI model has been applied to include a product acquisitions life cycle (Badiru, 2012), distance learning (DL) in graduate programs (Badiru and Jones, 2012), and a design for quality engineering (Badiru, 2014). One of the factors that make the DEJI model an effective systems engineering model is its use of both qualitative and quantitative assessment techniques throughout the process such as Pareto analysis and process mapping used in the design stage (Badiru and Jones, 2012). Another component that separates the DEJI model from other systems engineering models such as the V Model or Waterfall Model is its emphasis on integration as the final step in the structure of the system (Badiru and Jones, 2012).

The first stage of the DEJI model is the work design phase. In the design phase, activities such as planning, organising, and coordination of work elements take place to guide work designers into strategic thinking about work elements with a futuristic mindset instead of a mindset solely focused on the present needs of the system (Badiru and Bommer, 2017). The design stage uses two different product states to track the point-to-point transformations of the design: product state and produce state space (Badiru, 2014). The product state is a set of conditions that describe the product at a specified point in time, while the product state-space is the set of all possible states of the product lifecycle (Badiru, 2014). Product state can be measured by analysing the input and expected output of the system (Badiru, 2014). Product state-space can be measured by using mathematical models that use potential product state variables such as cost or operational efficiency (Badiru, 2014). The quantitative metric that can be used for the state-space is seen below (Badiru, 2014):

$$Z = f(z, x);\ Y = g(z, x) \tag{1}$$

Z = intermediate vector relating x to y

f = vector-valued function

z = output

x = input

g = vector-valued function

Y = output vector

For a product that transitions from one state to another, a driving function that creates a transitional relationship is seen below (Badiru, 2014):

$$Ss = f(x \mid Sp) + e \tag{2}$$

Ss = subsequent state

f = given action(s) applied to product

x = state variable

Sp = the preceding state

e = error component

The first mathematical model for state-space that can analyse which actions are needed to achieve the next desired product state while the second mathematical model allows one to see the effect of state variables on the product from going from one state to next which can be expanded into greater detail if needed (Badiru, 2014). The next mathematical model is used if a product (P) is described by state variables (s_i) where the composite state of the product can be represented at any time by the vector (**S**) containing P elements seen below (Badiru, 2014):

$$\mathbf{S} = \{s1, s2, \ldots, \mathrm{s}P\} \tag{3}$$

Lastly, the DEJI model includes a mathematical model that can be used to monitor state-by-state transformations using the mathematical model below (Badiru, 2014):

$$\mathbf{S}\mathrm{n} = \mathrm{Tn}\,(\mathbf{S}\mathrm{n}{-}1) \tag{4}$$

$\mathbf{S}\mathrm{n}$ = final state

Tn = transformation

All these quantitative models are further investigated in the next stage of the DEJI model, the evaluation stage.

Work evaluation evaluates the intended purpose of the work and its various work elements being done in the organisation (Badiru and Bommer, 2017). Like product state variables, the evaluation of a product can be done based on the cost, quality, schedule, and/or meeting requirements (Badiru, 2014). Another identified technique for product evaluation is learning curve productivity due to the measurement being based on the concept of growth and decay, which factors in half-life properties (Badiru, 2012). After the evaluation(s) has been concluded, justification of the program and its work element is needed (Badiru, 2014).

Figure 1 Design-evaluate-justify-integrate (DEJI) model (see online version for colours)

Source: Badiru and Bommer (2017)

The third stage of the DEJI model requires rigorous justification of the program and its work elements (Badiru and Bommer, 2017). The work justification stage is necessary to assure that errant and non-value added work elements are not added into the organisational pursuits (Badiru and Bommer, 2017). An important note for work elements is that a value-added work element does not just include work elements that generate physical products, but also adds value to the worker's well-being (Badiru and Bommer, 2017). The value of these work elements can be shown as a deterministic vector function to designate the value of both tangible and intangible attributes that characterise the project seen below (Badiru, 2014):

$$V = f(A1, A2, \ldots, Ap) \tag{5}$$

V = assessed value

A = quantitative measures or attributes

The basis of the justification stage is that all the work elements are necessary and not hampering the organisation's pursuits (Badiru and Bommer, 2017). The last stage of the DEJI model is the integration phase and without the integration phase, a system will be isolated and potentially worthless (Badiru, 2012).

The integration stage attempts to incorporate all the work elements that have been justified in the product system (Badiru and Bommer, 2017). All justified work elements of a system then must be properly integrated to align with the system's functional goals to remain sustainable for the organisation (Badiru, 2014). The DEJI model assures that sustainable work elements are the ones that fit within the flow of the organisation's operations (Badiru and Bommer, 2017). Without the integration of a new work element within the flow of the organisation's operations, the new work element will have short longevity (Badiru and Bommer, 2017). With the DEJI model, the model's structure makes it essential for the work elements to be associated with the organisation's end goals.

6.2 Implementation strategy for DEJI model in human factors for additive manufacturing

The strategy for implementing the DEJI model in human factors for additive manufacturing can follow similar applications of the DEJI model covered in the past. Like previous applications of the DEJI model, the start will be with the design phase by defining the product's state at specified points in time, and in this case, one would start with looking at the state of the operator during various parts in the 3D printing process (Badiru, 2014). The specified points in time for the human operator in the additive process would include the conceptualisation of the 3D model, the review, revision, and finalisation of the 3D model, the setup for printing of the 3D model, monitoring the product during the printing stage, cleaning the 3D printer and organising excess powder after the product has completed, filtering of the excess powder, and the post-process analysis of the product. With each of these specified points, the next step would be analysing the input and the expected output on each of these specified points using equation (1) to understand the state of the product with these state variables: product cost, final product due date, output quality, throughput, resource utilisation, and operational efficiency (Badiru, 2012).

Using equation (2) to measure the transitional relationship from one product state to another (Badiru and Racz, 2018), the state inputs include planning, defining, designing, revising, finalising, preparing, printing, and filtering, cleaning, machining, and analysing. The analysis of these state inputs will provide needed actions to advance to the next product state (Badiru, 2012). Next, equation (3) can describe the potential states of a 3D printed part from a 3D modelled part, and metal powder/plastic to a 3D printed part if more in- depth product analysis is needed (Badiru, 2014).

Following this potential product analysis, the last mathematical model used would be equation (4) to monitor state by state transformation using the state inputs previously listed and these outputs: product specifications, problem statement, 3D part layout, revised 3D part layout, final 3D part layout, machine setup, fabrication, reusable material, prepared machine, finalised part, and product complete (Badiru, 2014). After these design stage equations have been set up and calculated, the evaluation stage follows.

For human factors in additive manufacturing, the evaluation stage should include evaluating the operator's efficiency in successfully printing a quality part, and time needed to complete all tasks within the 3D printing process. An evaluation on these two metrics would allow for an analysis of the performance and mental workload of the human operator to see how the additive manufacturing process currently affects an operator and identify human factors issues in additive manufacturing and what tasks are having causing these issues to arise. An analysis of these will allow for additive manufacturing to explore solutions to these problems and how tasks can be adjusted to alleviate these issues, such as using more effective AI. Following this evaluation, these tasks require justification to assure that these are value-added activities.

The justification dimension of the DEJI model starts with justifying each task in the 3D printing process and making sure each task adds value, either tangible or intangible (Badiru and Racz, 2018). Using equation (5) to assess the value of these tasks by using quantitative measures such as operator efficiency, reliability, and part quality (Badiru, 2014). The other justification needed for human factors in additive manufacturing is the various precautions used in the 3D printing process, such as the PPE used to reduce static and oxygen monitoring for the room and filtration process (Shelton, 2019). These two justifications are needed to validate the implementation of DEJI model for human factors in additive manufacturing and continue onto the last stage of the DEJI model, the integration stage.

The integration of the DEJI model for human factors in additive manufacturing should be seamless with all the safety precautions already used in additive manufacturing. The system of 3D printing parts also revolves around the operator's ability to effectively design a 3D model that can successfully print and properly set up the 3D printer to make a fully functional replica of the 3D model, so maximising the human's performance is of the utmost importance. Some of the previous quantitative metrics used to do an effective assessment of the product state, such as cost and resource utilisation (Badiru, 2012). Following this strategy for implementing the DEJI model for human factors for additive manufacturing will help assure the additive manufacturing process is safe, user-friendly, and effective for human operators.

7 Conclusion

An overview of the literature to advance human-machine integration for improving the performance output in the additive manufacturing process was presented in this paper. This work begins with introducing the topics of additive manufacturing, cognitive ergonomics, and artificial intelligence. Then, it examines human considerations in the additive manufacturing process and how cognitive ergonomics support artificial intelligence techniques. Finally, case studies for the integration of human factors, cognitive ergonomics, and artificial intelligence are discussed. Also, the D-E-J-I systems engineering model for human-machine integration is examined. It is anticipated that the contents of this review paper will pave the way for further research into the integration of human factors and cognitive aspects in the future wave of AI in additive manufacturing.

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