Impact of Artificial Intelligence in South African Construction Project Management Industry

Siphosenkosi Makaula, Megashnee Munsamy, Arnesh Telukdarie
Post Graduate School of Engineering Management, University of Johannesburg
Johannesburg, South Africa
siphomakaula@gmail.com , arnesht@uj.ac.za

Abstract

The aim of this paper is to develop a framework for AI in construction management, to achieve this, a sequential literature review as the research methodology shall be used. Key words such as AI construction projects, labour productivity, project key success factors, construction project's job security and AI project risk management is used to search for published journal articles form Google Scholar and Scopus. The findings based on sequential literature review revealed that various AI technologies exists, and each has a different purpose and application. The research findings reveal application of each AI technology on each project life cycle phase. A theoretical framework based on the research findings is developed which illustrates the application of AI technologies across the project lifecycle and the results of each application. AI can be used in planning, design, simulation of construction projects, it can also be used in advanced project execution phases of construction as well as in sourcing of materials and modularisation of high-end and specialised construction material and modules. There is a threat of job losses in adopting AI, it is a reality and not a myth, however, AI can create plenty more jobs in the new technological value chain.

Keywords
Artificial Intelligence, Fourth Industrial Revolution, Construction Project Management,

1. Introduction and Background

1.1 Introduction

Artificial Intelligence in managing and executing construction projects is essential for project success. In the wake of Industry 4.0, it is imperative for Construction Project Management professionals to be equipped with technological tools that respond to global trends for competitiveness and relevance.

The paper aims to study the impact of the use of AI in construction projects. Artificial intelligence may be used in project planning, design and simulation, and in construction of modularised materials as well as in operating construction plant equipment. The findings from this study will improve the data in this area of study. The beneficiaries from this study are the construction project management professionals and the greater academia.

1.2 Background

Industry 4.0 also known as the Fourth Industrial Revolution (4IR) is a German strategic ingenuity, the purpose is to form smart factories in which industrial machineries are advanced, altered by Cyber-Physical Systems (CPS), the Internet of Things (IoT), Cloud Computing, Automation & Robotics and Artificial Intelligence (Zhong et al. 2017). In the years of 4IR, manufacturing systems are capable of monitoring physical activities, form the digital twins of the real world, and make logical choices using instantaneous message transmission and collaboration with people, machines and sensors (Zhong et al. 2017). 4IR point toward changes on how companies conduct their business and how they are organised (Tjahjono et al., 2017). 4IR describes the entire product lifespan: from idea development, production, operation and asset care and finally product reprocessing (Nowotarski and Paslawski, 2017)

In short, the Fourth Industrial Revolution brings about the transfer of processes and the management of processes that are usually managed by people into the internet cloud where further analysis and use can occur anywhere in the world (Paschek et al., 2017).

Artificial Intelligence (AI) is an area of research founded on the principle that intelligent thought can be viewed as a form of computation, one that can be formalized and eventually automated, for the achievement of that, however, two foremost issues require addressing, the two issues are knowledge representation and knowledge manipulation (Singh, Sarbjeet, 2010).

Artificial Intelligence is the philosophy and advancement of computer systems capable of executing activities ordinarily demanding human intellect, it also scrutinises by what method to capture and comprehend the logical conduct of computers, or in what way to answer predicaments with the use of computers that necessitate interoperability (Paschek et al., 2017). Pascheck et al (2017) stated that AI is sector of computer science, that emphases on examination of various problem areas such as robotics, flow text recognition, image, video and speech processing. AI is the art of constructing smart machines (Marwala, 2018). AI is a skill that advances philosophies, approaches, methods, and uses to broaden human smartness, it is relatively vast, it comprises numerous sections such as ML and PC optics. The general aim is to enable machines perform complex task that would ordinarily require human intelligence (Tan, 2018). Machines form part of day-to-day decision making, they are getting smarter due to Artificial Intelligence technology (Marwala; Hurwitz, 2017). AI is basically intellect demonstrated by devices, with logic (Aziz and Dowling, 2018). It is presumed that AI could render human race extinct or incapacitated in the next 100 years as devices with AI would overtake humans (Pan, 2016).

2. Sequential Literature Review

2.1 Role of Artificial Intelligence in Construction Project Life Cycle

AI applied in construction is a pragmatic instrument to examine and manage the sourcing of construction materials and skilled resources, other applications include logic-controlled tools for recording the logistics and waste produced in construction (Ginzburg et al., 2018). AI is also used in the distribution and transport of construction materials and products as well as in combating counterfeit construction products and materials (Ginzburg et al., 2018). Ginzburg et al (2018) goes on to say that Artificial intelligence can also be used as a practical tool for examination and policymaking protocol in the distribution department of a construction firm.

Artificial Intelligence is a technological innovation that allows manufacturing systems to learn from past experiences such that eventually there is the realisation of linked, smart, and ubiquitous business practice (Zhong et al., 2017).

Artificial Intelligence has a role to play in the construction management knowledge management. Knowledge, is categorized as unambiguous and inferred, within the building trade, unambiguous knowledge pertains to recorded data for instance project data, design blueprints and stipulations, financial data, safety assessments, all project data collected and kept in electronic format (Zhang et al., 2009). Inferred knowledge is the know-how kept in the workforce's mind, the corporate tenets, experiences, skill, intangible and worthwhile information (Zhang et al., 2009).

Artificial Intelligence has a role to play in design automation within the construction industry. Construction starts at the design stage of the built environment, the main contemplations of this stage is the development of automated design to expand cost effectiveness, improve the project life-cycle value, and allow interoperability amongst the project's lifecycle entities, and all these causes substantial cost savings (Neelamkavil, 2009). Consequently, He said, technology integration, with abilities in 3D design, systematic modelling and simulation and dispersed logic, suggests an excessive prospect to generate an cohesive and programmed design atmosphere (Neelamkavil, 2009).

Artificial Intelligence has a role to play in construction site automation. Robotics for logistics and assembly are used for automation in construction sites, nonetheless face countless constraints that are high-tech and financial in nature, robots face technological barriers in handling intricacies related to construction processes concerning live sites, collectively with the need for executing several activities with divergent features (Neelamkavil, 2009).

Artificial Intelligence has a role to play in virtual reality within the prefabricated construction modules. Virtual reality allows actual time viewing of, and interface with, data on spatial planning, the visualisation simulates execution of the activities as manufacturing, haulage, handling and assembly of components (Neelamkavil, 2009). It can also assess which components of the structure are to be assembled in what order, as well as reuse the model at varying stages of construction, crew members can imagine their precise activities and the relationships between the works of various other sub-contractors' components (Neelamkavil, 2009).

2.2 The Labour Productivity

Construction project success primarily rest on the administration of exceedingly interrelated contributions such as workers, material resources and financial resources (Kazaz and Acikara, 2015). Since the labour force differs from country to country, it presents doubts, thus, workers are difficult to manage. it is imperative to solve the causes affecting workers productivity to control workers successfully (Kazaz and Acikara, 2015).

Labour productivity is purely described as the quantity of work done by the workforce at a given time, labour productivity exerts a huge bearing on the time and the costs of a project, hence, for good project management issues touching labour productivity ought to be recognized (Kazaz and Acikara, 2015). Widespread research has been done to find qualitative and quantitative aspects manipulating labour productivity on site such as the climate, the scarcity of material and machinery, workers talents, inept guidance, poor technical drawings, worksite circumstances, geographic information, inadequate communication, workforce numbers, variation orders and delayed cash outflows (Muqeem et al., 2011).

With hindsight, all technological transformations have resulted in momentous economic growth (Schuh et al., 2015). The effect of 4IR is widespread and it impacts apart of production other support divisions, particularly engineering processes, that means that productivity growth potential predominantly rests in the enhancement of human smartness, policymaking processes and collaboration (Schuh et al., 2015). Economic growth as a result of construction projects is the focal indicator of productivity in the industry, it is unswervingly associated with workforce since it is the utmost vital, elastic resources used in projects, workforce performance is giuded by several aspects existing on site, it is difficult to consider these aspects when quantifying and valuating the production rates owing to uniqueness of each and every project (Muqeem et al., 2011; Aswed, 2016).

Chao (1994) cited in (Muqeem et al., 2011) stated that, various applications of Artificial Neural Network exist in the built environment industry for forecasting workforce performance, for example the excavation productivity rates and transportation time.

2.3 Impact of Artificial Intelligence on Job Security

Scholars project that by 2025 Artificial Intelligence would generate a market valued more than $35 billion with twofold yearly financial growth levels, projecting a future where humans and robots work hand in hand to respond to global intricacies together and equipped with voluminous computing and innovating power (Schoeman et al., 2017). South Africa, with a population of over fifty-five million people, businesses are overburdened by legacy technologies and systems, commercial models, bloated organisational structures, as well as being heavily invested in old-fashioned assets, all that accompanied by labour force that is not prepared for the Artificial intelligence revolution that has started globally, the workforce is anxious that AI will eradicate their jobs at worst pay disparity (Schoeman et al., 2017).

Although there is a perception that, AI introduction shall substitute or take some jobs, plenty more will be transformed into jobs that necessitate different skill-sets, whereas other totally new occupations will be created, plenty more occupations will continue to need exceptionally humans that Artificial Intelligence and machines cannot replicate, such as inventiveness, relationship, abstract and systems thinking, complex communication, and the capacity to work in diverse environments (Pillay, 2017).

Swift and fast-tracked digitisation will introduce economic interruptions rather than environmental interruptions, originating from notion that supercomputers become influential, businesses shall require few workers (David, 2015). Autor David (2015) continues to state that, technological development will leave behind some people, possibly more people, as it progresses. Autor David (2015) stated that workers with special skills and right education will benefit immensely from the new technological advancements. Conversely, He says, workers with ordinary or minimal skills and education will suffer a great deal as their jobs are more likely to be substituted by robots, automation and AI (David, 2015). Artificial Intelligence can discharge workforces from monotonous or hazardous activities or take away their livelihoods (Bughin et al., 2017). The introduction of novel technologies is guaranteed to interrupt production and labour markets, some skills will be outdated, meanwhile innovative talents may be essential to fulfil the enhanced technological climate (DeCanio, 2016; Etzioni and Etzioni, 2017). DeCanio (2016) further elaborates that, the rise in overall performance as a result of the technological change will cause growth in total output, associated with new business prospects and jobs.

There is vigorous indication that the technological transformation, starting with comprehensive use of computers and nowadays fast-tracked by AI, shall destroy several jobs: semi-skilled workers will be the first to be replaced by robots in occupations such as plant assembly lines, followed by administrative entry level workforce in banks and in professional services such as research in legal field (Etzioni and Etzioni, 2017). Morikawa (2017) suggested that skills gained through formal tertiary education in engineering and science complete the novel innovations of AI and robots, vocational skills that are task focused are unlikely to be impacted by AI.

David (2017) cited in (Morikawa, 2017) stated that, it is estimated that 55 - percent jobs are vulnerable to be substituted by computers in Japan. Similarly, Frey and Osborne (2017) cited in (Morikawa, 2017) emphasized that almost 47 percent of total US employment is faced with a treat of computerisation. Artificial intelligence is expected to a new supply value chain that will create new jobs (Morikawa, 2017). Notable, should there be strong consumer preference toward services provided by humans, it will be difficult to replace humans with Artificial intelligence (Morikawa, 2017).

Georgios Petropoulos cited in (Neufeind et al., 2018) argued that middle-level occupations that necessitate monotonous labour-intensive and cognitive skilled will be mostly affected by Artificial Intelligence, eventually, the initial labour change effects of occupations with routinised labour-intensive or cognitive skills, as in preceding industrial revolutions, shall be compensated for by the introduction of non-routine occupations in the newly formed technological era.

2.4 Project Risk Management

Risk Management is a methodical procedure of recognizing, examining and replying to risks, it is categorised by 6 stages: "planning", "risk identification", "qualitative risk analysis", "quantitative risk analysis", "risk response planning", "risk monitoring and control" (Irimia-Diéguez et al., 2014; Kutschenreiter-Praszkiewicz, 2018). Risk constitutes an important aspect of attention hence it can impact "cost-benefit analysis" in the complete development of a scheme, and the need, costs, duration (Irimia-Diéguez et al., 2014). Risk management is applied on all project lifecyle phases to be able to attain project goals (Rafindadi et al., 2014).

Project risk management encompasses processes, tools, and techniques that support the project manager to exploit the likelihood of outcomes of constructive actions and lessen the likelihood of consequences of hostile actions, project risk management is utmost effective when initially performed early in the project life cycle (Kutschenreiter-Praszkiewicz, 2018). AI helps “quantitative risk management” by observing the at risk parameters of a project, “machine learning” collectively with the “Monte Carlo simulation” helps project managers in “risk evaluation and simulation”, “fuzzy logic” is used to evaluate hazards in infrastructure projects to model “probability distributions” (Johnsonbabu, 2017). AI has acapacity to alert the project manager of risks real-time examination of project data (Johnsonbabu, 2017). Artificial Intelligence has introduced innovation in risk management, it improves understanding of unstructured data, and synthetizing approaches will provide a more elastic automated analytics approach (Dooley, 2017). Dooley (2017) argued that, most specialized Artificial Intelligence - driven applications are absorbed on areas in which Artificial intelligence can be used to scrutinize large volumes of data and find specific occurrences of behaviour.

From a risk management process point of view, artificial intelligence can support organisations at several phases ranging from “identifying risk exposure”, “measuring”, “estimating”, and “assessing its effects”, It can also aid in choosing suitable risk reduction policy and discovering tools that can facilitate risk transfer (Sanford and Moosa, 2015) cited in (Aziz and Dowling, 2018).

2.5 Project CSF

AI will aid project managers with growth in project value add by improving their determination in exploiting project accomplishments and release from monotonous functions, a project manager becomes available to work towards achieving project goals as set out in the project charter (Johnsonbabu, 2017).

It is predicted that projects generate one third of the global economy (Hadjinicolaou and Dumrak, 2017). The perceptible benefits of projects comprise of rise in sales, enhanced efficiencies, enhanced income limits and cashflows aided by improved income or falling expenses, imperceptible paybacks comprise areas of risk, enhancing client care, dealings with stakeholders, and business competence (Hadjinicolaou and Dumrak, 2017).

Cost overruns are harmful to project success, applying Artificial Intelligence in cost estimation maybe beneficial for a project. Cost overruns are identified as financial over expenditures, it comprises of unanticipated additional cost suffered owing to the errors in estimation of the projected budget of the project (Al-Hazim et al., 2017).

Project delays are also harmful to project success. Chan et al (1997), cited in (Al-Hazim et al., 2017) argued that, project delays was a result of five main causes, these causes are: “poor supervision and management of construction sites”, “unpredictable ground conditions of the project sites”, “unhurried procedures by decision-makers of the projects”, and “variation orders”, particularly requests done by the customers, deficiency of well-organised project strategies, “contracts and execution methods” and procedures.

2.6 Impact of AI on Labour Productivity and Job Security

Efficiency in built environment is frequently expressed as “production per workforce hour” (Pergamenshchik and Undozjorov, 2019). Given that labour represents a huge portion of cost and the amount of man-hours in execution of a job in construction is more sensitive to the impact of the executive than that of materials or money, this productivity gauge is regularly mentioned as workforce performance (Pergamenshchik and Undozjorov, 2019) Nevertheless, it is imperative to observe that workforce performance is a gauge to the total value of an functional technique in employing labour, equipment, and money to change labour endeavours into valuable products, and not the only measure of workforce competencies (Pergamenshchik and Undozjorov, 2019).

Speedy developments in Artificial Intelligence and Automation Technologies are likely to negatively interrupt labour markets, although Artificial Intelligence and Automation can increase the output of certain workforce, they can substitute and transform other occupations to some extent (Frank et al., 2019, p. 6531). Distinct from past technological innovations, AI has applications in a diversity of extremely scholarly, lucrative, and principally city-based industries such as health professions, finance, and information technology, even though technology largely results in a rise in productivity, AI has a potential to lessen current vital job prospects. (Frank et al., 2019).

Artificial intelligence is now well-thought-out by several authors as the developing force discouraging the capability of employees to preserve their position in the economy (Ashford and Hall, 2019; Arnone et al, 2019; Brynjolfsson and McAfee, 2014) cited in (Hall et al., 2019). Automation will possibly influence 1.2 billion occupations worldwide accounting for 14.6 trillion USD in earnings and 60.6 million occupations in United States, comparable to 2.3 trillion USD in earnings according to McKinsey Global Institute (2019) cited in (Hall et al., 2019). Automation is indiscernibly but inevitably creating displacements, skimming of unskilled labour from the workforce, the dislodged are flowing into mushrooming service jobs, these companies are conventionally disorganized that offer low pay scales with lengthier workdays (King, 2010) cited in (Hall et al., 2019).

AI has been an influential instrument in the built environment in the last 10 years, various AI modeling techniques have been used in the construction industry for example, expert systems (ES) and Artificial Neural Network (ANN) (Golnaraghi et al., 2019).

Construction projects are extremely vibrant with several trials in the areas of costs, interruptions and disturbances, diminished productivity, quality problems, safety characteristics, materials scarcity, and escalation, these trials are very complex in their make-up and data associated with these challenges is ambiguous (Golnaraghi et al., 2019). As a result, built environment works are within the ambit of ANN in which the known vague data can be efficiently decoded in order to reach a telling deduction, simply put, since ANN’s are capable to illustrate the associations concerning input and output stipulated through a training dataset (Golnaraghi et al., 2019). ANN is appropriate for nonsequential problems where ambiguous data, biased judgment, skill, and site conditions are crucial features, and old methods are inadequate to compute the intricate input-output relationship essential for predicting construction labour productivity (Golnaraghi et al., 2019).

2.7 Impact of AI on Construction Projects Life Cycle

The construction industry is under-digitized, with corporations unable to apprehend the capacity of AI as a driver of progress and effectiveness; applying AI entails substantial capital spending for construction firms, but the returns can dwarf the preliminary expenditure Mckinsey cited in Hepton (2019). The introduction of 3D planning transformed construction design and currently, building information modelling (BIM) has once more changed the development. BIM permits everybody concerned in a construction project to gain access to project data on one design platform in Hepton (2019).

“Estimation at Completion” is the executive’s prediction of total life cycle cost the end, it is a vital instrument for observing project efficiency and risk (Al Hares and Budayan, 2019, p. 1). Management often make executive decisions on projects, nonetheless, lack practical know-how which result in errors in their decisions (Al Hares and Budayan, 2019, p. 1). Al Hares and Budayan (2019) executed new fixed intelligence models, that is, “global harmony search” (GHS) and “brute force” (BF) combined with “extreme learning machine” (ELM) for modeling the project construction EAC.

2.8 Impact of AI on Project Risk Management

Construction projects risk can be assessed using fuzzy logic which basically shapes the likelihood distributions (Johnsonbabu, 2017) cited in (Basaif et al., 2018). Fuzzy approaches are largely used in construction projects for risk assessment (Basaif et al., 2018, p. 42). To this end, machine learning is yet to be harnessed extensively for risk examination in construction projects, regardless of utilising it for other jobs in construction projects such as discovering best project tendering strategy and measuring the subcontractors and suppliers’ performances (Basaif et al., 2018, p. 42).

3. Research Methodology

The research methodology used is a sequential literature review (SLR). Key words such as artificial intelligence, construction projects, labour productivity, project key success factors, construction project’s job security and AI project risk management is used to search for published journal articles form Google Scholar and Scopus. The intention is to find literature that addresses the application and impact of AI in construction projects specifically as it pertains to labour productivity, job security and project risk management.

4. Research Findings

Table 1 shows the application of each identified Artificial Intelligence technology in construction projects. The findings based on sequential literature review revealed that various AI technologies exists, and each has a different purpose and application. The research findings revealed application of each AI technology on each project life cycle phase as illustrated in Figure 1.

Table 1: Research Findings illustrating justification for each AI technology application (Source: Author)

Artificial Intelligence Technology	Application	References
AI - Knowledge Management	Design data, budgets, specifications, technical drawings, data collection, storage	(Zhang et al., 2009). (Zhong et al., 2017), (Jang et al., 2019), (Lan et al., 2018)
Fuzzy Logic	Initial project scoping, preliminary and feasibility studies, baseline risk assessments	(Basaif et al., 2018), (Johnsonbabu, 2017), (Le et al., 2019), (del Caño et al., 2016), (Ju et al., 2016)
Monte Carlo Simulation	Baseline risk assessments, project risk assessments	(Johnsonbabu, 2017), (del Caño et al., 2016), (Ju et al., 2016), (Salling and Leleur, 2017)
3D Design Technology	Modelling and simulation	(Benotsmane et al., 2019), (Neelamkavil, 2009), (Štefanič and Stankovski, 2018), (Tan, 2018)
Building Information Modelling (BIM)	Modelling, simulation, integrated project management toolkit	(Carbonari et al., 2019), (Capocchiano and Ravanelli, 2019); (Bongiorno et al., 2019), (Neelamkavil, 20090, (Hepton , 2019), (Tan, 2018), (Chen et al., 2018);
Monte Carlo Simulation	Modelling and simulation	(Salling and Leleur, 2017), (del Caño et al., 2016), (Ju et al., 2016)
Robots	Substitute for human operators for high risk activities	(Neelamkavil, 2009), (David, 2015), (Bhugin et al., 2017), (Schoeman et al., 2017), (Chen et al., 2018)
Automation	Machine automation using logic systems	(Ginzburg et al., 2018), (Huang and Liao, 2019), (Bumpei and Yashiro, 2019)
Artficial Neural Networks (ANN)	Productivity forecasting, modelling	(Chao, 1994), (Muqeem et al., 2011), (Golnaraghi et al., 2019)
Expert Systems	Modelling	(Golnaraghi et al., 2019), (Islam et al., 2019), (Hadj-Mabrouk, 2019)
Drones	Remote surveillance, unmanned autonomous vehicles (UAV)	(Murugesan et al., 2019), (Mondal and Syryamkin, 2019), (Rubio et al., 2019), (Paulino et al., 2019),
Virtual reality	Visual simulation, augmented reality	(Neelamkavil, 2009), (Benotsmane et al., 2019), (Tan, 2018)

5. Theoretical Framework

A theoretical framework model supported by the research finding illustrates the application of AI technologies across the project life cycle. AI Technologies application in construction project life cycle differs per life cycle phase and required phase output. The resultant output of AI technology application per life cycle phase is indicated on Figure 1 as for example, increased labour productivity, well-informed project risk management, crisis or dilemma or conflict in policy pertaining to job security and preservation and technological advancements, project key success factors attainment from the application of various AI technologies.

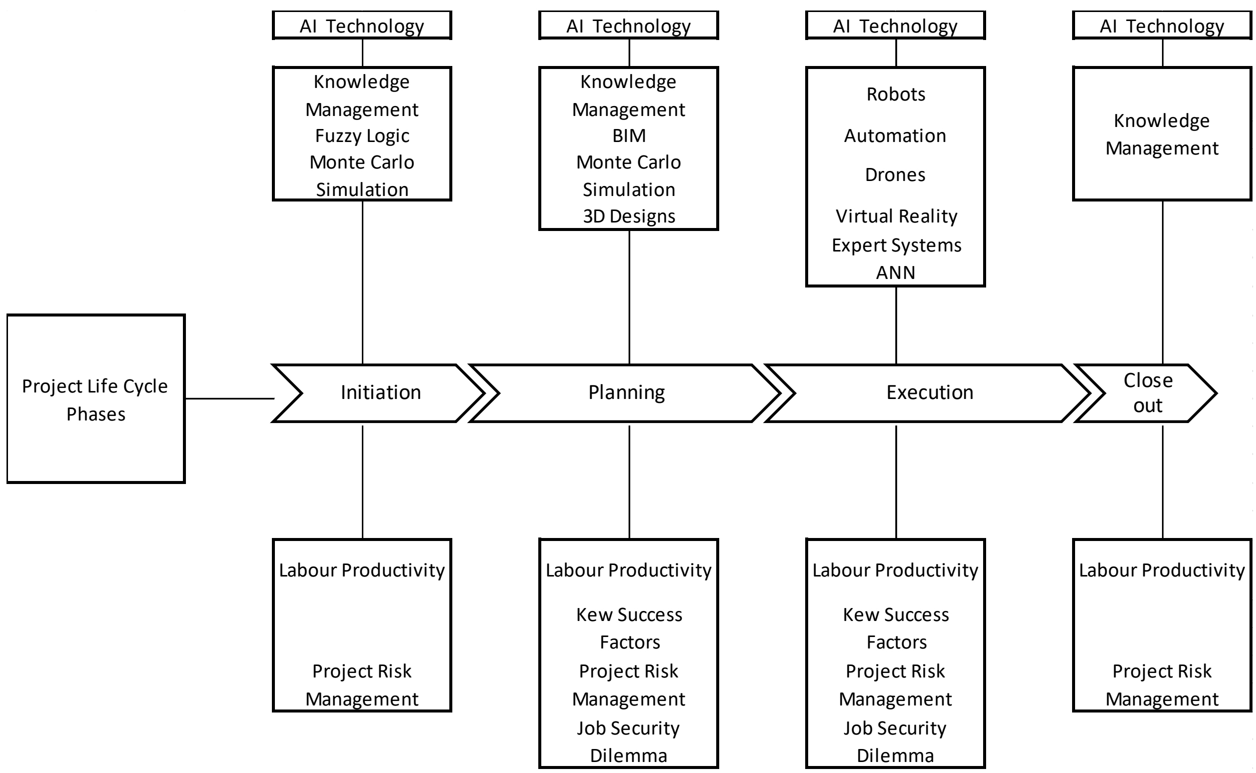

Figure 1: Theoretical Framework developed from the research Findings
(Source: Author)

6. Conclusions

Application of Artificial intelligence in the construction industry is important, especially in the wake of the global trend of the Fourth Industrial Revolution. Artificial Intelligence can be used in planning, design, simulation of construction projects, it can also be used in advanced project execution phases of construction as well as in sourcing of materials and modularisation of high-end and specialised construction material and modules. Artificial intelligence can reduce the risk of accidents in construction sites and loss of life. High risk activities can be automated using Artificial Intelligence technology. Human error in judgement, bias, nepotism and corruption can be reduced or eliminated by adopting Artificial Intelligence to assist in decision-making.

There is a threat of loss of human jobs in adopting Artificial intelligence, it is a reality and not a myth, however, Artificial Intelligence can create plenty more jobs in the new technological value chain. South Africa and the greater African continent in general lack behind in technological innovations chiefly because of the obvious under development and economic growth struggle. To catch up, technological innovations need to be introduced especially in the high growth construction sector as Africa is a developing continent.

7. References

Al Hares, E.F.T., Budayan, C. Estimation at completion simulation using the potential of soft computing models: Case study of construction engineering projects. Symmetry (Basel). 11. https://doi.org/10.3390/sym11020190 . 2019

Al-Hazim, N., Salem, Z.A., Ahmad, H. Delay and Cost Overrun in Infrastructure Projects in Jordan. Procedia Eng. 182, 18–24. https://doi.org/10.1016/j.proeng.2017.03.105. 2017

Alvi, M., A manual for selecting sampling techniques in research. Univ. Karachi, Iqra Univ. 55. 2007

Aswed, G.K. Productivity Estimations Model for Bricklayers in Al- Qadisiyah, Journal For Engineering Sciences, 9, 183–199. 2016

Aziz, S., Dowling, M.M. AI and Machine Learning for Risk Management. SSRN Electron. J. https://doi.org/10.2139/ssrn.3201337. 2018

Basaif, A.A., Loo, S.C., Alashwal, A.M. A Review on the Application of Artificial Intelligence for Risk Analysis in Construction Projects. Proc. ASEAN Post Grad. Conf. 2018, Univ. Malaya, Kuala Lumpur, 15 November. 2018. 2018

Benotsmane, R., Kovacs, G., Dudas, L. Economic, Social Impacts and Operation of Smart Factories in Industry 4.0 Focusing on Simulation and Artificial Intelligence of Collaborating Robots. Soc. Sci. 2019

Bongiorno, N., Bosurgi, G., Carbone, F., Pellegrino, O., Sollazzo, G. Potentialities of a Highway Alignment Optimization Method in an I-BIM Environment. Period. Polytech. Civ. Eng. 63, 352–361. https://doi.org/10.3311/ppci.12220. 2019.

Bumpei, M., Yashiro, T. Research on inefficiency analysis method of building energy utilizing time series data. IOP Conf. Ser. Earth Environ. Sci. 294, 012052. https://doi.org/10.1088/1755-1315/294/1/012052. 2019

Bughin, J., Brussels, Hazan, E., Ramaswamy, S., Chui, M., Allas, T. Investing in an Age of Technology Disruption Background Information. Discussion Paper. June 2017. Mackinsey Global Institute. 2017

Campbell, K. The Fourth Industrial Revolution is upon us and South African industry must adapt. URL http://www.engineeringnews.co.za/article/the-fourth-industrial-revolution-is-upon-us-and-south-african-industry-must-adapt-2017-10-27/rep_id:4136 (accessed 4.3.19). 2017

Capocchiano, F., Ravanelli, R.. AN ORIGINAL ALGORITHM FOR BIM GENERATION FROM INDOOR SURVEY POINT CLOUDS. Int. Arch. Photogrammetry. Remote Sens. Spat. Inf. Sci. Vol. XLII-2/W13, 2019 ISPRS Geospatial Week 2019, 10–14 June 2019, Enschede, Netherlands XLII, 10–14. 2019

Carbonari, A., Corneli, A., Di Giuda, G.M., Ridolfi, L., Villa, V. A decision support system for multi-criteria assessment of large building stocks. J. Civ. Eng. Manag. 25, 477–494. https://doi.org/10.3846/jcem.2019.9872. 2019

Chen, X., Chen, Q., Zhang, Z., Cheng, Y., Qi, Z. BIM+ Robot Creates a New Era of Building Construction. J. Phys. Conf. Ser. 1069. https://doi.org/10.1088/1742-6596/1069/1/012142. 2018

David, H.A. Why are there still so many jobs? The history and future of workplace automation. J. Econ. Perspect. 29, 3–30. https://doi.org/10.1257/jep.29.3.3. 2015

DeCanio, S.J. Robots and humans – complements or substitutes? J. Macroecon. 49, 280–291. https://doi.org/10.1016/j.jmacro.2016.08.003. 2016

del Caño, A., Pilar de la Cruz, M., Gómez, D., Pérez, M. Fuzzy method for analysing uncertainty in the sustainable design of concrete structures. J. Civ. Eng. Manag. 22, 924–935. https://doi.org/10.3846/13923730.2014.928361. 2016

Dooley, B Risk Management Meets AI. https://tdwi.org/articles/2017/08/11/adv-all-risk-management-meets-ai.aspx [Accessed: 21 April 2019]. 2017

Etzioni, A. and Etzioni, O. Should Artificial Intelligence Be Regulated? Issues in Science and Technology; Washington Vol. 33, Iss. 4, (Summer 2017): 32-36. 2017

Frank, M.R., Autor, D., Bessen, J.E., Brynjolfsson, E., Cebrian, M., Deming, D.J., Feldman, M., Groh, M., Lobo, J., Moro, E., Wang, D., Youn, H., Rahwan, I. Toward understanding the impact of artificial intelligence on labor. Proc. Natl. Acad. Sci. U. S. A. 116, 6531–6539. https://doi.org/10.1073/pnas.1900949116. 2019

Ginzburg, A., Kuzina, O., Ryzhkova, A. Unified resources marking system as a way to develop artificial intelligence in construction. IOP Conf. Ser. Mater. Sci. Eng. 365. https://doi.org/10.1088/1757-899X/365/6/062021. 2018

Golnaraghi, S., Zangenehmadar, Z., Moselhi, O., Alkass, S., Vosoughi, A.R. Application of Artificial Neural Network(s) in Predicting Formwork Labour Productivity. Adv. Civ. Eng. 2019. https://doi.org/10.1155/2019/5972620. 2019

Hadjinicolaou, N., Dumrak, J. Investigating Association of Benefits and Barriers in Project Portfolio Management to Project Success. Procedia Eng. 182, 274–281. https://doi.org/10.1016/j.proeng.2017.03.191. 2017

Hadj-Mabrouk, H. Contribution of Artificial Intelligence to Risk Assessment of Railway Accidents. Urban Rail Transit 5, 104–122. https://doi.org/10.1007/s40864-019-0102-3. 2019

Hall, R.P., Ashford, R., Ashford, N.A., Arango-quiroga, J. Universal Basic Income and Inclusive Capitalism: Consequences for Sustainability. 2019

Hepton, J. The future of AI in the construction industry. https://www.techradar.com/news/the-future-of-ai-in-the-construction-industry . 2019

Huang, L., Liao, S. Structural Performance Analysis of Wall Climbing Robot. IOP Conf. Ser. Mater. Sci. Eng. 569, 042006. https://doi.org/10.1088/1757-899x/569/4/042006. 2019

Irimia-Diéguez, A.I., Sanchez-Cazorla, A., Alfalla-Luque, R. Risk Management in Megaprojects. Procedia - Soc. Behav. Sci. 119, 407–416. https://doi.org/10.1016/j.sbspro.2014.03.046. 2014

Islam, R.U., Ruci, X., Hossain, M.S., Andersson, K., Kor, A.-L. Capacity Management of Hyperscale Data Centers Using Predictive Modelling. Energies 12, 3438. https://doi.org/10.3390/en12183438. 2019

Jang, I., Lee, D., Choi, J., Son, Y. An approach to share self-taught knowledge between home IoT devices at the edge. Sensors (Switzerland) 19. https://doi.org/10.3390/s19040833, 2019

Johnsonbabu, A. Reinventing the role of Project manager in the Artificial intelligence era Theme: Project Management Leadership-> In a Rapid changing world. Proj. Management Natl. Conf. India 1–11. 2017

Ju, Y., Zhang, C., Ma, L. Artificial intelligence metamodel comparison and application to wind turbine airfoil uncertainty analysis. Adv. Mech. Eng. 8, 1–14. https://doi.org/10.1177/1687814016647317. 2016

Kazaz, A., Acikara, T. Comparison of Labor Productivity Perspectives of Project Managers and Craft Workers in Turkish Construction Industry. Procedia Comput. Sci. 64, 491–496. https://doi.org/10.1016/j.procs.2015.08.548. 2015

Kutschenreiter-Praszkiewicz, I. Application of Artificial Intelligence in Project Management Under Risk Condition. Univ. Bielsk. Dep. Ind. Eng. Bielsk. Pol. 69–80. 2018

Lan, L., Liu, Y., Feng Lu, W. Learning from the Past: Uncovering Design Process Models Using an Enriched Process Mining. J. Mech. Des. Trans. ASME 140. https://doi.org/10.1115/1.4039200. 2018

Le, L.M., Ly, H.-B., Pham, B.T., Le, V.M., Pham, T.A., Nguyen, D.-H., Tran, X.-T., Le, T.-T. Hybrid Artificial Intelligence Approaches for Predicting Buckling Damage of Steel Columns Under Axial Compression. Materials (Basel). 12, 1670. https://doi.org/10.3390/ma12101670. 2019

Marwala, T. The limit of artificial intelligence: Can machines be rational? 1–22. 2018

Marwala, T. and Hurwitz, E. Artificial Intelligence and Economic Theories. Adv. Inf. Knowl. Process. 2017

Mondal, M., Syryamkin, S.I. Gesture based terrain mapping and recognition-overview. IOP Conf. Ser. Mater. Sci. Eng. 516. https://doi.org/10.1088/1757-899X/516/1/012050. 2019

Morikawa, M. Who Are Afraid of Losing Their Jobs to Artificial Intelligence and Robots? Evidence from a Survey, GLO Discussion Paper, No. 71, Global Labor Organization (GLO), Maastricht. 2017

Mourtzis, D. et al. ‘Cyber- Physical Systems and Education 4.0 -The Teaching Factory 4.0 Concept’, Procedia Manufacturing. Elsevier B.V., 23(2017), pp. 129–134. doi: 10.1016/j.promfg.2018.04.005. 2018

Muqeem, S., Idrus, A.B., Khamidi, M.F., Zakaria, S. Bin. Prediction Modeling of Construction Labor Production Rates using Artificial Neural Network. 2011 2nd Int. Conf. Environ. Sci. Technol. IPCBEE 6, 32–36. 2011

Murugesan, R., Sudarsanam, S.K., Malathi, G., Vijayakumar, V., Neelanarayanan, V., Venugopal, R., Rekha, D., Saha, S., Bajaj, R., Miral, A., Malolan, V. Artificial Intelligence and Agriculture 5. 0. Int. J. Recent Technol. Eng. 8, 1870–1877. https://doi.org/10.35940/ijrte.b1510.078219. 2019

Nahod, M.-M. and Radujković, M. V. M. ‘The Impact of ICB 3.0 Competences on Project Management Success’, Procedia - Social and Behavioral Sciences, 74, pp. 244–254. doi: 10.1016/j.sbspro.2013.03.014. 2013

Neufeind, M., O`Reilly, J., Ranft, F. Praise for Work in the Digital Age. Rowman & Littlefield International Ltd. London. 2018

Neelamkavil, J. 3-Automation in the prefab and modular construction industry Automation in the Prefab and Modular Construction Industry. Int. Symp. Autom. Robot. Constr. ISARC 2009, Austin, Tex. June 24-27. 2009

Nowotarski, P. and Paslawski, J. 'Industry 4.0 Concept Introduction into Construction SMEs', IOP Conference Series: Materials Science and Engineering, 245(5). doi: 10.1088/1757-899X/245/5/052043. 2017

Osunsanmi, T., Aigbavboa, C., Oke, A., Ohiomah, I. Construction 4.0: Its impact towards delivering quality and sustainable houses in South Africa 147–156. https://doi.org/10.3311/ccc2018-020. 2018

Pan, Y. Heading toward Artificial Intelligence 2.0. Engineering 2, 409–413. https://doi.org/10.1016/J.ENG.2016.04.018. 2016

Paschek, D., Luminosu, C.T., Draghici, A. Automated business process management – in times of digital transformation using machine learning or artificial intelligence. MATEC Web Conf. 121, 04007. https://doi.org/10.1051/matecconf/201712104007. 2017

Paulino, Â.D.C., Guimarães, L.N.F., Shiguemori, E.H. Hybrid Adaptive Computational Intelligence-based Multisensor Data Fusion applied to real-time UAV autonomous navigation. Intel. Artif. 22, 162–195. https://doi.org/10.4114/intartif.vol22iss63pp162-195. 2019

Pereira, A. C. and Romero, F. 'A review of the meanings and the implications of the Industry 4.0 concept', Procedia Manufacturing. Elsevier B.V., 13, pp. 1206–1214. doi: 10.1016/j.promfg.2017.09.032. 2017

Pergamenshchik, B., Undozjorov, V. A model of the labor productivity dependence on workforce density. E3S Web Conf. 97, 1–8. https://doi.org/10.1051/e3sconf/20199706020. 2019

Pillay, N. Artificial Intelligence for Africa: An Opportunity for Growth, Development, and Democratisation. Computer Science Department, University of Pretoria. 2017

Rafindadi, A.D., Mikić, M., Kovačić, I., Cekić, Z. Global Perception of Sustainable Construction Project Risks. Procedia - Soc. Behav. Sci. 119, 456–465. https://doi.org/10.1016/j.sbspro.2014.03.051. 2014

Rubio, F., Valero, F., Llopis-Albert, C., 2019. A review of mobile robots: Concepts, methods, theoretical framework, and applications. Int. J. Adv. Robot. Syst. 16, 1–22. https://doi.org/10.1177/1729881419839596. 2019

Salling, K.B., Leleur, S. Transport project evaluation: feasibility risk assessment and scenario forecasting. Transport 32, 180–191. https://doi.org/10.3846/16484142.2015.1063003. 2017

Schoeman, W., Moore, R., Seedat, Y., Y.J, C. Artificial intelligence: Is South Africa ready? Accenture – Gordon Institute of business Science, University of Pretoria. 2017

Schuh, G., Potente, T., Wesch-Potente, C., Weber, A.R., Prote, J.P. Collaboration mechanisms to increase productivity in the context of industrie 4.0. Procedia CIRP 19, 51–56. https://doi.org/10.1016/j.procir.2014.05.016. 2014

Schumacher, A., Erol, S. and Sihn, W. 'A Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises', Procedia CIRP. The Author(s), 52, pp. 161–166. doi: 10.1016/j.procir.2016.07.040. 2016

Singh, Sarbjeet, S.S. Artificial Intelligence .pdf. Int. J. Comput. Appl. 6, 21–23. 2010

Štefanič, M., Stankovski, V. A review of technologies and applications for smart construction. Proc. Inst. Civ. Eng. Civ. Eng. 172, 83–87. https://doi.org/10.1680/jcien.17.00050. 2018

Sukamolson, S. Fundamentals of quantitative research Suphat Sukamolson, Ph.D. Language Institute Chulalongkorn University. Fundam. Quant. Res. 1–20. 2005

Sveikauskas, L. et al. 'Productivity Growth in Construction', Journal of Construction Engineering and Management, 142(10), p. 04016045. doi: 10.1061/(asce)co.1943-7862.0001138. 2016

Tan, K. The Framework of Combining Artificial Intelligence and Construction 3D Printing in Civil Engineering. MATEC Web Conf. 206, 01008. https://doi.org/10.1051/matecconf/201820601008. 2018

Tjahjono, B. et al. 'What does Industry 4.0 mean to Supply Chain?', Procedia Manufacturing. Elsevier B.V., 13, pp. 1175–1182. doi: 10.1016/j.promfg.2017.09.191. 2017

Zhang, X., Mao, X., AbouRizk, S.M. Developing a knowledge management system for improved value engineering practices in the construction industry. Autom. Constr. 18, 777–789. https://doi.org/10.1016/j.autcon.2009.03.004. 2009

Zhong, R.Y., Xu, X., Klotz, E., Newman, S.T. Intelligent Manufacturing in the Context of Industry 4.0: A Review. Engineering 3. https://doi.org/10.1016/J.ENG.2017.05.015. 2017

Biographies:

Siphosenkosi Makaula is a PhD candidate at the Post Graduate School of Engineering Management at the University of Johannesburg in South Africa. He earned an MBA degree and a B-Tech degree in Mechanical Engineering. He is registered as Professional Engineering Technologist and Professional Construction Health & Safety Manager. He is the Chief Executive of Makaula & Associates (Pty) Ltd an engineering consultancy that specializes in engineering & project safety management in the infrastructure and oil & gas industries in South Africa.

Arnesh Telukdarie is a senior academic at the University of Johannesburg. He holds a PhD in Chemical Engineering and is a registered Professional Engineering Technologist. He has over 20 years of industrial experience in Manufacturing systems and business Optimization systems. Professor Telukdarie has many international peer-reviewed journal publications and conference proceedings. Professor Telukdarie is a consulting engineer in engineering management, Business Optimization, and Systems.