Effects of Fourth Industrial Revolution Biotechnological Drivers on Construction Occupational-Related Diseases in Nigeria

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Abstract

The persistence of diseases that affect the construction workforce as a result of activities on construction sites poses a danger to the sustainable development of the industry. This resulted in a huge loss of skilled labour and economic development for the entire country. The emergence of the fourth industrial revolution (4IR) technologies calls for a need to assess the effect of the technology's biological driver on construction occupation-related diseases. Therefore, this study assessed the effect of genome sequencing and neurotechnology on construction occupation-related diseases in Northern Nigeria. The study is quantitative in design through the administration of 650 questionnaires to project managers and health and safety (H&S) managers in the three geopolitical zones of Northern Nigeria using a proportionate sampling technique. A total of 400 were duly completed, representing a 61.5% response rate. The collected data was analyzed using the Warp PLS-SEM 8.0 software algorithm. The study found that the effects of the 4IR's biological driver variables ranged from moderate to high effects for genome sequencing (GENSE) and neurotechnology (NEURO), respectively. The combined predictive relevance of the two (2) variables predicts 64% of the construction occupation-related diseases. This implies that the adoption of the driver would help reduce the causes of construction-related diseases. The study recommends the adoption of the 4.0IR biological driver for the management of construction occupation-related diseases on construction sites for proper transformation of the sites.

Keywords: *Biotechnology, Construction-related diseases, Fourth Industrial Revolution, Nigeria, Questionnaire survey.*

Introduction

The construction industry has always put a high value on the H&S of the workforce as a central tenet of project performance (Karthick, Kermanshachi, and Ramaji, *et al*., 2022; Gambo, Said, & Ismail, 2017). However, several studies have revealed that the construction industry is one of the most hazardous industries, with high rates of fatalities, injuries, and other health-associated problems (Aalto-Korte, Koskela, and Pesonen., 2020; Ringen *et al*., 2014).

Health problems due to occupation-related diseases cause many problems for projects in terms of productivity and performance. Teixeira *et al*. (2021) stated that occupational-related diseases are health problems that are attributable to exposure to occupational risk factors in the workplace. Pega *et al*. (2021) viewed occupational disease as any disease contracted primarily as a result of exposure to risk factors arising from work activity.

Work-related diseases have multiple causes, and factors in the work environment may play a role, together with other risk factors, in the development of such diseases. The issues of poor management, human elements, and poor working conditions were identified as the main factors triggering occupational-related diseases (Bevan, 2015). Karthick *et al*. (2022) further observed that shortages in the supply of proper technological tools and equipment, lack of responsibility, negligence of safety precautions among the workforce, and workforce resistance to safety practices are the main factors triggering occupational-related diseases.

Previous studies have shown that heatstroke, eye strain, lung irritation, skin disease, backache, musculoskeletal disorders, hearing loss, skin problems, breathing problems, occupational lung diseases, and cancer are the major types of H&S ailments in the construction industry (Karthick *et al*., 2022; Aalto-Korte *et al*., 2020). Baxter *et al*. (2010) classified the construction occupation-related diseases in the construction industry into six (6) categories: asbestos-related diseases, silica-related diseases, noise-induced hearing loss, hand-arm vibration syndrome, musculoskeletal disorders, and dermatitis.

According to Stucken and Hong (2014) and Dobie (2008), occupational hearing loss is the most common occupational disease in the United States (US), and it is often accepted as a normal consequence of employment. More than 30 million workers are exposed to hazardous noise, and an additional nine million are at risk from other traumatic agents. In the United Kingdom (UK), musculoskeletal disorders (MSD) are the main occupational ailment (Bevan, 2015). Similarly, Ekpenyong and Inyang (2014) reported that 39.25% of construction occupation-related diseases in Nigeria are attributed to work-related musculoskeletal disorders, which are the most prevalent in the country.

However, in South Africa, cardio-respiratory tuberculosis (CRTB) is the most prevalent occupational disease, at 40.55% (Theodore *et al*., 2015). While noise-induced hearing loss is the second most prevalent occupational disease, with a prevalence rate of 32.36%, additionally, pneumoconiosis (15.37%) and silicosis (14.51%) were also noted to be prevalent (Teixeira *et al*., 2021).

The Fourth Industrial Revolution (4IR) is a term coined in 2016 by Klaus Schwab. It is not limited to industrial production; it is manifested in all aspects of society, including technology. The fundamental technological drivers of the Fourth Industrial Revolution entail the development of digital, physical, and biological technologies. Breakthroughs in biotechnological development driven by the 4IR are centred on genetic technology and neurotechnology (Li, Hou, and Wu, 2017). Genetic study is one of the most vibrant branches of biological research. With the advancements in computing supremacy, significant development has been achieved in reducing the cost and increasing the ease and efficiency of genetic sequencing, activating, and editing (Chou, 2018).

Genome sequencing is the process of using recombinant DNA (rDNA) technology to alter the genetic makeup of an infected workforce. Li *et al*. (2017) reported that previously it took more than a decade and cost 2.7 billion USD to complete the Human Genome Project (HGP), but recently, with the advancement in computer technology, a genome can be sequenced in a few hours for less than 1000 USD.

For the treatment of construction-occupation-related diseases, IBM's Watson supercomputer system is used to provide personalized treatment plans for cancer patients by comparing the historical data obtained from the worker, and treatments made. This provides genetic information with updated medical knowledge in just a moment. In addition, progress in genetic engineering helps the workforce achieve higher productivity yields by enhancing the robustness, effectiveness, and productiveness of a work site.

On the other hand, neurotechnology is used to monitor brain activity and study how the brain changes and interacts with complex working environments like construction sites. The goal of neurotechnology is to confer the performance edge of human systems on robotic machines (Delcomyn, 2007). Floreano, Ijspeert, and Schaal (2014) revealed that the combination of information and artificial intelligence technology applications in brain sciences has been increasing gradually. There are neuroimaging and neurostimulation devices that enhance disease treatments (Li *et al*., 2017).

The application of neurotechnology by the construction industry is used to treat occupation-related ailments such as paralysis and control the activities of prosthetic limbs with minds for productivity improvement at the site (Roelfsema, Denys, and Klink, 2018). Neurofeedback, the technology to monitor brain activity in real-time, offers countless opportunities to help fight addictions, regulate food behaviour, and improve performance in a work environment. As for medical treatment, being able to collect, process, store, and compare large amounts of brain activity-related data allows the improvement of the diagnosis and treatment efficiency of occupation-related brain disorders and mental health-related issues (Ramirez-Zamora *et al*., 2018).

Generally, the application of biotechnology can create innovative and sophisticated solutions to a wide range of problems. Therefore, there is a need to assess the effects of 4IR biotechnological drivers (genome sequencing and neurotechnology) on construction occupation-related diseases in the Nigerian construction sector of the economy.

The objectives of this study are:

- To identify factors triggering construction-occupation-related diseases among the workforce.
- To assess the effects of 4IR biotechnological drivers (genome sequencing and neurotechnology) on construction occupation-related diseases among the Nigerian workforce.

Literature Review

Causes of Construction Occupation-related Diseases

A construction occupation-related disease is any disorder of structure or function in the body of a construction worker, especially one that produces specific symptoms or that affects a specific location and is not simply a direct result of physical and mental-related injuries (Gambo & Musonda, 2022; Hämäläinen, Takala, and Saarela, 2007).

McTernan, Dollard, and LaMontagne (2013) further defined occupation-related disease as any illness caused or made worse by workplace factors. This includes many diseases that have more complex causes involving a combination of occupational and non-work-related factors. Previous studies revealed that the major occupation-related diseases and health problems in the construction industry are heatstrokes, eye strain, lung irritation, skin disease, MSDs, hearing loss, cancer, stress, mental health disorders, and respiratory ailments such as silicosis, asthma, and so on (McTernan *et al*., 2013; Burdorf, Dahhan, & Swuste, 2003).

Kamardeen (2021) reported that the main causes of construction occupation-related diseases are the effects of hazardous substances such as dust that emanates from certain types of construction activities, chemicals, and potentially harmful mixtures that are common in construction sites. According to Bowen, Edwards, and Lingard (2013), the main causes of occupational-related diseases are exposure to long working hours, workplace exposure to air pollution, asthma agents, carcinogens, ergonomic risk factors, and noise.

Lopes, Haupt, and Fester (2011) and Al-Kindi, Brook, Biswal, and Rajagopalan (2020) opined that the key risk factors triggering diseases in the construction industry are exposure to long working hours and exposure to air pollution. McTernan *et al*. (2013) reported that the main causes of construction occupation-related disease are work processes that emit dust, fumes, vapours, or gases into the air that affect the lungs. According to Kamardeen (2021), the majority of ill health in the construction industry is a result of overworking and unacceptable pressures.

According to Burdorf, Dahhan, and Swuste (2003), the main causes of diseases in construction sites are maltreatment and intimidation of the workforce, while Kamardeen (2021) observed that frequent harassment of the workforce is the main cause of stress in the construction workforce. In addition, Chung (2021) argued that other major causes of diseases in construction sites arise from the long-term operation of vibratory equipment, noise, and heavy manual work. Moreover, Gupta

(2021) showed that construction occupation-related diseases are mostly caused by exposure to a variety of agents, including primary irritants or sensitizers, physical agents, and mechanical trauma caused by repetitive movement.

McTernan *et al*. (2013) viewed biological agents (bacteria, fungi, etc.) as the main causes of diseases at construction sites. Kamardeen (2021) stated that occupational MSDs are the major illnesses among construction workers in South Africa that are caused by common repetitive movements, which include injuries such as carpal tunnel syndrome and medial or lateral epicondylitis. Occupation-related diseases strain health systems, affect productivity, and ultimately affect the economy of a nation (McTernan *et al*., 2013).

Construction occupation-related diseases were responsible for the deaths of thousands of workers in 2016, of which the construction industry in developing countries had the largest proportion (Takala *et al*., 2017). The majority of occupation-related deaths were due to respiratory and cardiovascular diseases; non-communicable diseases accounted for 81% of occupation-related deaths (Herbert and Landrigan, 2000). The same author reported that the greatest causes of death in the UK construction industry are chronic obstructive pulmonary diseases. Moreover, in 2019, the United States experienced a rise in the death rate from occupation-related diseases (Wang, 2021).

Adekunle, Umanah, Adewale, and Egege (2018) reported that the most common causes of occupation-related deaths in the Nigerian construction industry were due to exposure to harmful substances or environments. Additionally, in South Africa, Hnizdo, Esterhuizen, Rees, and Lalloo (2001) reported that the issue of ill health kills and ruins lives in the construction industry and described that a construction workforce is at least 100 times more likely to die from a disease that has been caused or exacerbated by the work than from a fatal accident. Construction work itself is regarded as stressful, tough, hazardous, highly manual, and transient in nature. Further to these conditions, approximately 30% of the workforce is transient in nature (Takala *et al*., 2017).

Genome Sequencing a 4IR Biological Driver.

The 4IR's biological driver is centred on genome sequencing and neurotechnology (Chung, 2021). Genome sequencing is the process of using recombinant DNA (rDNA) technology to alter the genetic makeup of an infected workforce. The application of genetic technologies in the areas of stem cells, cloning, gene therapy, genetic manipulation, gene selection, sex selection, and preimplantation diagnosis has created a significant opportunity for improved H&S in the construction workforce (Greenhill *et al.*, 2021).

Genetically engineered bacteria and other microorganisms are currently used to produce human insulin, human growth hormone, and a protein used in blood clotting for injured construction workers (Lund, 2021). One of the first cases of human benefit from genome sequencing was the production of human insulin in bacterial cells (Greenhill *et al.*, 2021). With the successful production of genetically engineered insulin, many other human proteins have been produced in this manner. This technology improved millions of lives in lives in the workforce (Lund, 2021).

More recently, it has become possible to develop therapeutic molecules that can target occupation-related diseases such as cancer by genome sequencing of naturally occurring antibodies (Chung, 2021). These antibodies may have toxic molecules attached to them to kill cancer cells or may be modified to improve their sticking to the cancer cells and activate the patient's immune system to destroy cancer (Lund, 2021).

A breakthrough in genome sequencing has been the ability to sequence the DNA in cancer cells of a construction worker (Land *et al.*, 2015). The process of genome sequencing entails the identification of which genes and mutations aid in developing medicines for the cure of certain occupation-related ailments. Recently, genome sequencing has impacted the stratification of cancer, the characterization of genetic diseases, and the provision of information about a worker's likely response to treatment.

In addition, for construction workers experiencing ill health conditions, DNA sequencing provides a precise diagnosis that might affect the medical management of symptoms or provide treatment options (Punina, Makridakis, Remnev, and Topunov, 2015). Generally, genome sequencing provides information concerning drug efficacy or its effects.

Similarly, through the analysis of workforce DNA, a specific gene variant that predisposes a worker to certain ailments based on working conditions was identified and treated (Quainoo *et al.*, 2017). However, the high cost of establishing and maintaining a sequencing facility, the lack of skilled personnel, limited access to tools for genomic data manipulation and analysis, and the lack of a regulatory framework are some of the major factors influencing the establishment of genetic engineering laboratories on construction sites (Punina *et al*., 2015).

Land *et al*. (2015) stated that the main factors influencing genome sequencing in construction sites are obtaining scientific information with potential medical implications, the technical accuracy of the system, and the protection of information.

Quainoo *et al*. (2017) argued that lifetime use of the system and cascading testing to other family members are the major factors influencing the genome sequencing of workers in the construction environment. They added that information of value to future generations in workers' families as well as staying ahead of nongenetic healthcare providers as the most important factors influencing genome sequencing at the construction sites.

However, Land *et al*. (2015) added that the sense of empowerment, psychological benefits, and cost-saving are the major factors influencing genome sequencing in the construction industry.

Neurotechnology of the 4IR Biological Driver

Neurotechnology refers to any technology that provides greater insight into brain or nervous system activity and affects brain or nervous system function (Xing *et al*., 2020). Based on the nature of the construction working environment, workers most likely experience brain cancer and other types of mental diseases.

Neurotechnology is purely based on research purposes that experiment with brain imaging to gather information about mental illness or the sleep patterns of the workforce (Yang *et al*., 2021). The common goals of neurotechnology are neural activity readings that control external devices such as neuroprosthetics, altering neural activity via neuromodulation that restores or normalizes functions affected by neurological disorders because of poor site conditions, or augmenting cognitive abilities (Umer *et al*., 2018).

The application of natural sensors in the bodies of construction workers was degenerated by diseases or decoupled by traumatic injuries, muscles, or organs that no longer obtain neural input. Neurotechnology offers alternatives to pharmaceutical approaches and devices for diseases that have been fatal (Xing *et al*., 2020). The pharmaceutical products that contain nanoparticles, which improve absorption within the bodies of workers, provided a remedy for this situation. Neurotechnology provides a means of using chemotherapy drugs on the affected cancer cells (McKiernan, 2017).

Teigland, van der Zande, Teigland, and Siri (2018) stated that neurotechnology allowed stimulation of deeper regions of the brain than other techniques of treatment for workers with good spatial resolution. This system is cheap and portable and also provides good signal quality for easy identification of diseases.

While McKiernan (2017) stated that the system is used to diagnose and screen different mental illnesses and causes, Yang *et al*. (2021) stated that the system provided an easy drug delivery system, health monitoring, and the production of vaccines.

Also, Xing *et al*. (2020) stated that neurotechnology provided an interface between the brain of a workforce and a computer for easy control of assistive devices, phrenic and bladder pacemakers, spinal cord stimulators to treat pain, vision prostheses, grasp, and gait neuroprostheses after a stroke or spinal problem.

Theoretical Framework

This study adopted two (2) theories: the Scientific Management Theory and Schumpeter's Innovation Theory. The two (2) theories tend to explain the relationship between the application and use of technology in H&S services, i.e., the application of technology for the identification, control, and curing of certain kinds of occupation-related diseases.

The scientific management theory was developed by Frederick Taylor (2004), which posits that a scientific method should be used to perform tasks in the workplace, as opposed to the leader relying on their judgment or the personal discretion of team members. The theory explains that scientific and technological methods like the 4IR's biological driver can reduce occupation-related diseases.

On the other hand, Schumpeter's Theory of Innovation is in line with other business investment theories, which assert that the change in business investment accompanied by monetary expansion is the major factor behind business improvement. Schumpeter's Theory posits that business innovation is the major reason for minimizing cause-and-effect relationships, hence improving productivity in investments and business success. The two theories can be used to explain the relationship between the study constructs, i.e., the two dimensions of the 4IR's biological driver (genome sequencing and neurotechnology) and the construction occupation-related disease considered in this study. Hence, the theories advocate the adoption of technology to minimize the cause-and-effect relationship and improve business productivity.

Research Method

This study reviewed past literature on the 4IR biological driver and construction occupation-related diseases. The variables identified from previous literature were used to adapt a structured questionnaire that was used to collect data on the three (3) study constructs, consisting of two (2) constructs of the 4IR biological driver (independent variables) and one (1) construct on the construction occupation-related diseases (dependent variable). Thus, the study design was quantitative (McNabb, 2017).

The study covered three geopolitical zones of Northern Nigeria (North-West, North-East, and North-Central). A total of 650 questionnaires were administered to experienced project managers and H&S managers working with the construction industry in the three geopolitical zones using a proportionate sampling technique. Four hundred and sixty-two (462) of the questionnaires were returned as completed, of which sixty-two (62) were rejected because of inconsistencies in the responses. Thus, the duly completed questionnaires were 400, representing a 61.5% response rate.

The questionnaires had closed-ended questions only. The questions used in this study were captured by the three (3) constructs, namely: construction occupation-related diseases (CORED) as the dependent variable, genome sequencing (GENSE), and neurotechnology (NEURO) as factors of the 4IR biological driver (independent variables), respectively. All the variables were measured on a 5-point Likert scale. Through the development of a model, partial least squares structural equation modelling (PLS-SEM) was used to analyze the data obtained and examine the effects of the path model between the constructs.

Hair *et al*. (2019) suggested that PLS-SEM facilitates theory building in studies that seek to explore causal relationships between latent variables rather than the covariance-based structural equation modelling (CB-

SEM) that is generally used to confirm theories. Moreover, PLS-SEM was employed for the analysis because of its high predictive ability and for examining the validity of reflectively measured constructs. The measurement model of the conceptual framework is depicted in Figure 1, and it shows the number of items in each construct. Table 1 indicates the sources from which the items of each construct were adapted.

Conceptual Framework

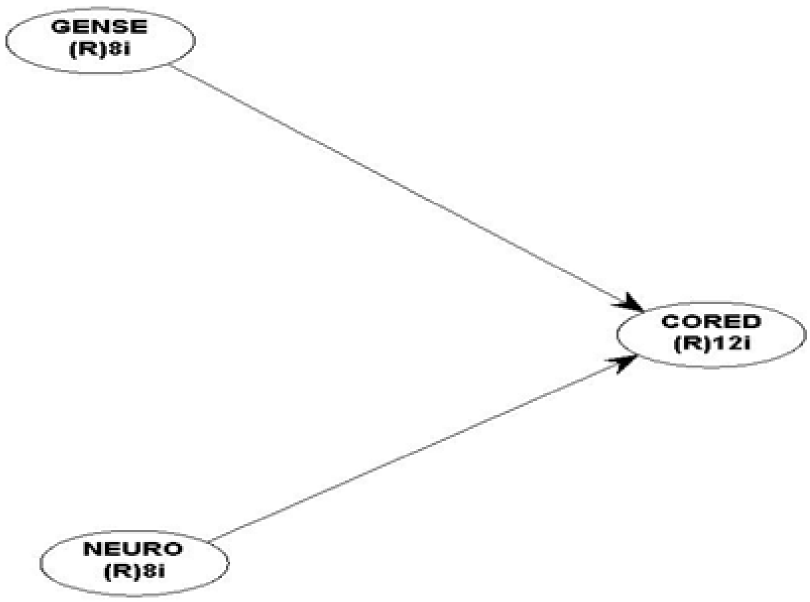

Figure 1: Measurement Model

Based on the measurement model in Figure 1, the following directional alternate hypotheses were developed:

H_{A1}: There is a significant high effect between the genome sequencing of the 4IR biological driver (GENSE) and the construction occupation-related diseases in Nigeria.

H_{A2}: There is a significant moderate effect between the neurotechnology of the 4IR biological driver (NEURO) and construction occupation-related diseases in Nigeria.

Table 1. Development of the construct for the study

S/N	CONSTRUCTS	SOURCE
CORED	**Factors Reducing Construction Occupational-Related Diseases**	
CORED 1	Easing repetitive movement	McTernan *et al*., (2013); Burdorf *et al*., (2003)
CORED 2	Improving setting up of workstations	Hämäläinen *et al* ., (2007); Kamardeen, (2021)
CORED 3	Improve sanitary condition	Burdorf, *et al*., (2003), Chung (2021)
CORED 4	Correcting poor design of tools	Kamardeen, (2021); Chung (2021)
CORED 5	Eliminating hazardous dust	Chung (2021); Gupta (2021)
CORED 6	Eliminating hazardous chemicals	Gupta (2021); Takala *et al*., (2017)
CORED 7	Controlling biological agents (insects, reptiles, animals)	Bowen *et al*., (2013); Kamardeen, (2021)
CORED 8	Controlling working temperature	Takala *et al*., (2017); Gupta (2021)
CORED 9	Minimizing unacceptable pressure and attacks	Baxter, *et al*., (2010); Bowen *et al*., (2013)
CORED 10	Heavy overwork	Wang, (2021); Kamardeen, (2021)
CORED 11	Minimizing maltreatment of worker	Lopes, *et al.,* (2011); Gupta (2021)
CORED 12	Elimination of heavy noise	Al-Kindi *et al*., (2020); Kamardeen, (2021)
GENSE	**GENOME SEQUENCING**	
GENSE 1	Analyzing of worker's DNA for a specific gene variant that may predispose workers to certain ailment as a result of working condition	Land *et al*., (2015); Quainoo *et al*., (2017)
GENSE 2	Precise diagnosis of occupationally related diseases	Punina *et al*., 2015); Chung (2021)
GENSE 3	Characterization and stratification of occupationally related disease	
GENSE 4	Information on workers' likely response to diseases	Quainoo *et al*., (2017) Chung (2021)
GENSE 5	Information on drug efficacy or its effects	Greenhill *et al*., (2021); Quainoo *et al*., (2017)
GENSE 6	Advancement in the development of medicines for workers	Chung (2021); Quainoo *et al*., (2017)
GENSE 7	Access to scientific information on different occupational diseases	Lund (2021); Chung (2021)
GENSE 8	Technical accuracy of the system	Chung (2021); Quainoo *et al*., (2017)
NEURO	**NEUROTECHNOLOGY**	
NEURO 1	Provides brain imaging for information relating to the mental health of workers	Xing *et al*., (2020); Umer *et al*., (2018)
NEURO 2	Controlling external devices (neuroprosthesis) to aid workers	Yang *et al*., (2021); McKiernan, (2017)
NEURO 3	Augmenting cognitive abilities	Umer *et al*., (2018); Lund (2021)
NEURO 4	Aiding natural sensors of the body of workers	McKiernan, (2017); Lund (2021)
NEURO	Nanoparticles aid infected workers to	Teigland *et al*., (2018); McKiernan,

The research constructs that were identified from the extant literature cover construction occupation-related diseases and the two (2) dimensions of the biological drivers of the 4IR. They are all measured using the 5-point Likert scale with one-dimensionality. The construction occupation-related diseases, which are the dependent variable, were operationalized from very severe to very severe.

The independent constructs (dimensions), i.e., the genome sequencing and neurotechnology dimensions of 4IR, were operationalized using very low to very high effects. The operationalization process was adapted from the studies of Gambo and Musonda (2021a) and that of Gambo and Musonda (2021b)

Results

Respondents' Demographic Information

Table 2 shows the respondents' demographic information. The results in Table 2 indicated that 58.25% of the respondents were 4IR-experienced project managers working in the construction sector in Northern Nigeria. While 41.75% of the respondents were 4IR experienced H&S managers working in the region, All the respondents hold at least a bachelor's degree in construction-related disciplines. Only 10% of the respondents are PhD holders, and 44% have Master's degrees, while 46% of the respondents hold Bachelor's degrees as their highest educational qualification. This shows that all the respondents are educationally qualified to respond to a questionnaire of this nature, which enhances the validity of the research data. Also, Table 2 revealed that the study respondents have an average of 12 years of working experience in the H&S practice; this implies that the professionals are very experienced in the area of this research.

Table 2: Respondents Demographic Information

Project Managers	No.	%	Cumulative %	
Project Managers	233	58.25	58.25	
H&S Managers	167	41.75	100	
Total	400	100		
Educational Qualifications				
PhD	38	10.00	10.00	
MSc	178	44.00	54.00	
BSc	184	46,00	100	
Total	400	100		
Years of Experience				
Years	Mid Value (x)	Frequency (f)	% of Frequency	fx
5-10	7.5	126	31.50	945.00
10-15	12.5	147	36.75	1837.50
15 and above	15.0	127	31.75	1905.00
Total		400	100	4687.50

Mean of years of experience Σfx/Σf = 4687.50/400 = 12 years' mean experience

Indicators of Model Fit

Table 2 shows the respondents' demographic information. The results in Table 2 indicated that 58.25% of the respondents were 4IR-experienced project managers.

Previous studies (Hair, Risher, Sarstedt, and Ringle, 2019; Kock, 2017) provided basic sets of guidelines on the information that should be included in the reports on confirmatory factor analysis as the primary statistical analysis technique. Such indices include Chi-square, Alike Information Criteria (AIC), Comparative Fit, Parsimonious Fit, Goodness-of-Fit Index, Standardized Root Mean Square Residual (SRMR), Bentler-Bonett or Normed Fit Index, and Root Mean Square Error (RMSE) (Hair *et al*., 2019). However, Kock (2017) stated that there are theoretically straightforward differences between CB-SEM and PLS-SEM; when the research is about theory testing and confirmation, the best method is to use CB-SEM.

However, if the research is about prediction and theory development, the suitable method is to use PLS-SEM. Conceptually and practically, PLS-SEM is similar to multiple regression analysis. On the interpretation of the model fit, if the goal is to only test hypotheses, where each arrow represents a hypothesis, then the model fit indices are of little importance. However, if the goal is to find out whether one model has a better fit with the original data than another, then the model fit indices are useful sets of measures related to model quality (Kock, 2017).

The fit indices are used to compare the indicator correlation matrices such as the standardized root mean squared residual (SRMR), standardized mean absolute residual (SMAR), standardized chi-squared (SChS), standardized threshold difference count ratio (STDCR), and standardized threshold difference sum ratio (STDSR).

As with the classic model fits and quality indices, the interpretation of these indices depends on the goal of the SEM analysis. Since these indices refer to the fits between the model-implied and empirical indicator correlation matrices, they become more meaningful when the goal is to find out whether one model has a better fit with the original data than another, particularly when used in conjunction with the classic indices (Kock, 2017).

When assessing the model's fit with the data, several criteria are recommended, as follows: The average path coefficient (APC) was 0.436 with a P-value $\leq$ 0.001, the average R-squared was 0.637 with a P-value $\leq$ 0.001, and the average adjusted R-squared (AARS) was 0.635 with a P-value $\leq$ 0.001. The average block VIF (AVIF) = 1.633, acceptable if $\leq$ 5, ideally $\leq$ 3.3, hence regarded as ideal. The average full collinearity VIF (AFVIF) = 2.402, acceptable if $\leq$ 5, ideally $\leq$ 3.3, hence regarded as ideal. The VIF is used when indicators are formative. Tenenhaus GoF (GoF) = 0.527, small $\geq$ 0.1, medium $\geq$ 0.25, large $\geq$ 0.36, then GoF is regarded as large, The GoF is the geometric mean of the average communality (outer measurement model), and the average R^2 of endogenous latent variables represents an index for validating the PLS model globally, as it looks for a compromise between the performance of the measurement and the structural model, respectively. The Sympson's paradox ratio (SPR) = 1.000, acceptable if $\geq$ 0.7, ideally = 1, and regarded as ideally.

Therefore, all the fit indices are acceptable in this study. The R-squared contribution ratio (RSCR) = 1.000, acceptable if $\geq$ 0.9, ideally = 1, is regarded as ideal in this study. The statistical suppression ratio (SSR) is 1.000, which is acceptable if $\geq$ 0.7, so it is acceptable in this study. Nonlinear bivariate causality direction ratio (NLBCDR) = 1.000, acceptable if $\geq$ 0.7, which is regarded as acceptable in this study.

The standardized root mean square residual (SRMR) value for this model was 0.07, which indicated a good fit (Hu and Bentler, 1999). The Bentler-Bonett or Normed fit index was 0.98, which was considered good (Bentler and Bonett, 1980). The Root Mean Square Error (RMSE) for this model was 0.05 and was regarded as good, according to Fadlelmula (2011). Therefore, this model has a good fit index.

Measurement Model

Table 3 shows the assessment of the model by the WarpPLS 8.0 algorithm, which typically follows two steps: the assessment of reflective measurement and structural models (Hair *et al*., 2019). The assessment of the measurement model examines the validity and reliability of the measurement instrument and the relationship among the constructs. The model for this study has three reflective constructs: construction occupation-related diseases (CORED) (dependent variable), 4IR biological genome sequencing (GENSE), and 4IR biological neurotechnology (NEURO) (independent variables). The reflective measurement model evaluates the reliability and validity of the model.

The two criteria are composite reliability (CR) and the average variance extracted (AVE) (Hair *et al*., 2019). Ho (2006) stated that the reliability of a measuring instrument is defined as its ability to consistently measure the phenomenon it is designed to measure. Reliability, therefore, refers to a test of consistency. The importance of reliability lies in the fact that it is a prerequisite for ensuring research instrument consistency.

This study used the Cronbach's alpha (α) test to test the reliability of the research instrument. Ho (2006) recommended Cronbach's alpha test as the most reliable among others. According to Benjamin *et al*. (2018), Cronbach's alpha (α) test is used for the questionnaire's construct consistency and level of random error. The use of Cronbach's alpha allows the negative construct to be detected and the positive to be accepted, ranging from 0.0 to 1.0 scales. The minimum acceptable value for Cronbach's alpha is 0.6 (Ho, 2006). Hence, the items to be used for this study must be within the benchmark value of reliability indicators.

Therefore, the indicator and construct reliability were used to evaluate the reliability of the reflective measurement model for structural equation modelling. The indicator reliability was evaluated by cross-checking the loading of each indicator variable on its associated latent construct, and the loading should be higher than 0.70 before accepting the reliability of the indicator variable (Hair *et al*., 2019). For the assessment of construct reliability, two coefficients are considered, i.e., composite reliability and Cronbach's alpha (Schmidt and Bohannon, 1988). Hair *et al*. (2019) recommended CR for PLS-SEM.

Table 3 shows the results of the measurement model for this study, which indicated high internal consistency and reliability. The indicator loadings were all > 0.70, and the CR and Cronbach's ranges were 0.899–0.846 and 0.873–0.791, respectively. This shows that all the indicators and constructs' reliability is acceptable.

Convergent and discriminant validity are also considered in the validation of the reflective measurement model (Hair *et al*., 2019). The average variance extracted (AVE) values of the constructs must be greater than 0.5 for acceptable convergent validity (Hair *et al*., 2019). The AVE is only applicable to models with reflective indicators. AVE measures the total variance of a construct through its indicators (Ho, 2006). The AVE values for this study ranged between 0.556-0.510; these are all higher than the benchmark of 0.500. Therefore, the convergent validity of the measurement model is acceptable (Davcik, 2014).

Table 3: Results of the Measurement Model Evaluation

Construct	Items	Factor Loading	CR	Cronbach's α	AVE
CORED	CORED 1	0.937	0.899	0.873	0.544
	CORED 2	0.922			
	CORED 3	0.878			
	CORED 4	0.778			
	CORED 5	0.912			
	CORED 6	0.728			
	CORED 7	0.931			
	CORED 8	0.742			
	CORED 9	0.959			
	CORED 10	0.749			
	CORED 11	0.781			
	CORED 12	0.832			
GENSE	GENSE 1	0.911	0.846	0.791	0.510
	GENSE 2	0.754			
	GENSE 3	0.711			
	GENSE 4	0.977			
	GENSE 5	0.758			
	GENSE 6	0.739			
	GENSE 7	0.831			
	GENSE 8	0.934			
NEURO	NEURO 1	0.781	0.867	0.823	0.556
	NEURO 2	0.922			
	NEURO 3	0.758			
	NEURO 4	0.774			
	NEURO 5	0.954			
	NEURO 6	0.838			
	NEURO 7	0.766			
	NEURO 8	0.821			

Note: α-alpha; CR-composite reliability; AVE- average variance extracted

Table 4 indicates the discriminant validity of the measurement model. Discriminant validity is the extent to which a construct is distinguished from other constructs in the model (Hair *et al*., 2019). This is achieved by checking the AVE of each construct, which must be higher than the highest squared correlation of the construct with any other construct in the model, or the loading of an indicator with its associated construct must be higher than that with other constructs (Fornell and Larcker, 1981). The results indicated that the square root of AVE for each construct, with its correlation to another construct, is acceptable for the discriminant validity of the measurement model. Based on the results of the measurement model, the questionnaires were recognized to be reliable and valid for the assessment of the study constructs.

Table 4: Results for Discriminant Validity

	CORED	GENSE	NEURO
CORED	**0.768**		
GENSE	0.667	**0.640**	
NEURO	0.648	0.623	**0.676**

Note: Discriminant validity showing AVE

Measures and Path Coefficients of the Model

Figure 2 indicates the R^2 measure of endogenous latent variables (constructs) and the path coefficients of the model. The model is evaluated as part of a preliminary assessment of structural relationships, i.e., the inner model and hypothetical framework (Hair *et al*., 2019). Therefore, Chin (1998) suggested 0.67, 0.33, and 0.19 as substantial, moderate, and weak measures for R2, respectively. The R^2 for this study is 0.64, which indicates that a moderate relationship exists between the criterion and predictor variables. The path coefficient between GENSE and CORED also has a β-value of 0.60 with a P-value of < 0.01 significant at the 0.05 level of significance. Similarly, the path coefficient between NEURO and CORED has a β-value of 0.28 with a P-value < 0.01, which is significant at the P-value 0.05 level of significance.

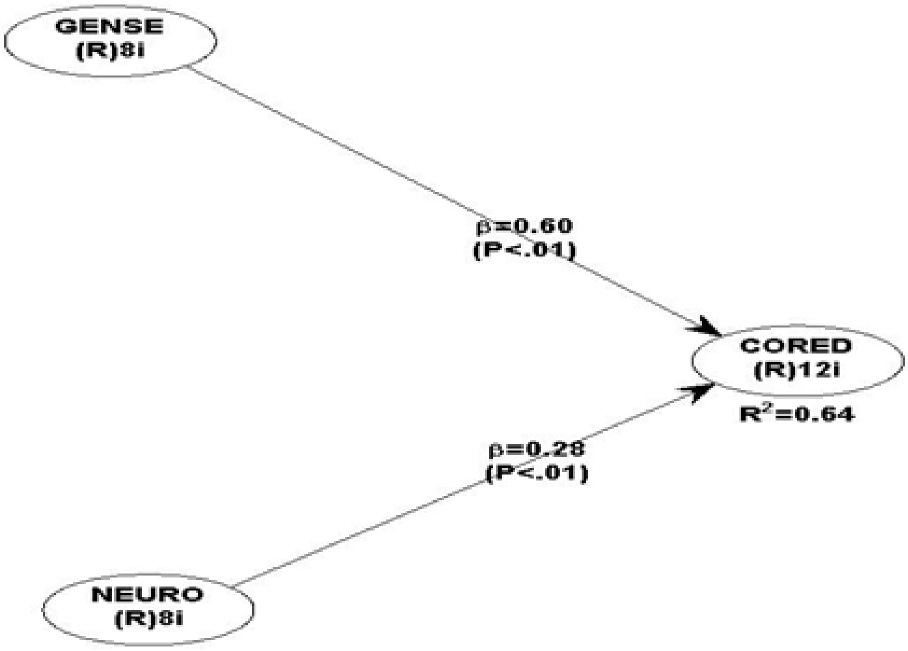

Figure 2: Assessment results for the structural model

Table 5 indicates the effect size (f^2), which is a measure that confirms whether the effects indicated by the path coefficients are low, moderate, or high for the values of f^2 of 0.02, 0.15, and 0.35, respectively (Cohen, 1988). Effect size (f^2) indicates the effect of a certain construct on the dependent latent variable is substantial (Chin, 1998).

The f^2 between GENSE and CORED is 0.46, which indicates a high effect size. The f^2 between NEURO and CORED is 0.18, indicating a moderate effect size. The predictive competency of each endogenous construct in the model was determined by Stone-Geisser's (cross-validated redundancy) (Q^2) (Hair *et al*., 2019). The predictive skill (Q^2) of this model is 0.64.

Hair *et al. (2019)* reported that Q^2 values indicate the predictive relevance as either weak (0.02), moderate (0.15), or strong (0.35). Therefore, this model exhibits strong predictive relevance. Consequently, the path model's predictive relevance to the endogenous construct is strong. This implies that the two predictors of CORED (GENSE and NEURO) predict 64% of the variance of the dependent variable.

Table 5: Hypotheses-Testing Results

Hypotheses	Path coefficient	P-value	Effect size (f^2)	Stone-Geisser's Q^2	R^2	Supported
GENSE? CORED	0.60	<0.01	0.46	0.64	0.64	Yes
NEURO? CORED	0.28	<0.01	0.18			Yes

Note: Level of significance (p) ≤ 0.05; Q^2-cross-validated redundancy

Graphical Relationships among the Study Constructs

Figure 3 presents a graph of the relationship between GENSE and CORED. The graph indicates that a linear relationship exists between the two (2) constructs. The relationship implied a positive relationship, which means that the adoption of GENSE would improve the construct of CORED. The coordinates' points (x_o, yo,and x_1, y_1) and the regression line of the graph were (2.00, 2.83, and 4.85, 4.64). The mean score value of CORED was 4.09 with a standard deviation (SD) of 0.55. On the other hand, the construct GENSE had a mean score value of 3.97 and an SD of 0.82.

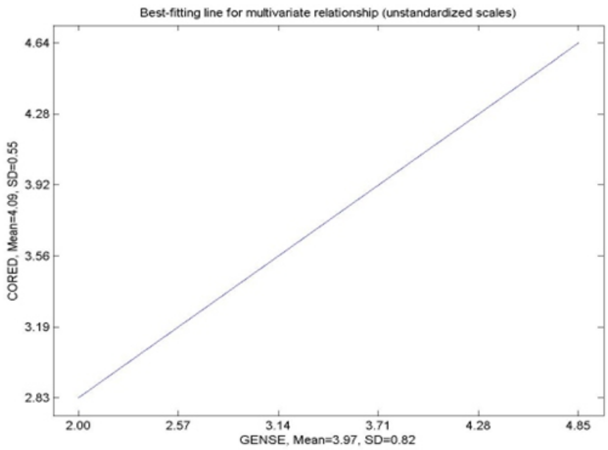

Figure 3: Relationship of GENSE and CORED

Figure 4 presents a graph of the relationship between the adoption of NEURO and CORED. The graph indicates that a linear relationship exists between the two (2) constructs. The relationship implied a positive relationship, which means that the adoption of NEURO would improve the construct of CORED. The coordinates' points (x_o, yo, and x_1, y_1) and the regression line of the graph were (1.94, 3.54, and 5.00, 4.31). The mean score value of CORED was 4.09, with a standard deviation (SD) of 0.55. On the other hand, the construct GENSE had a mean score value of 4.13 and an SD of 0.93.

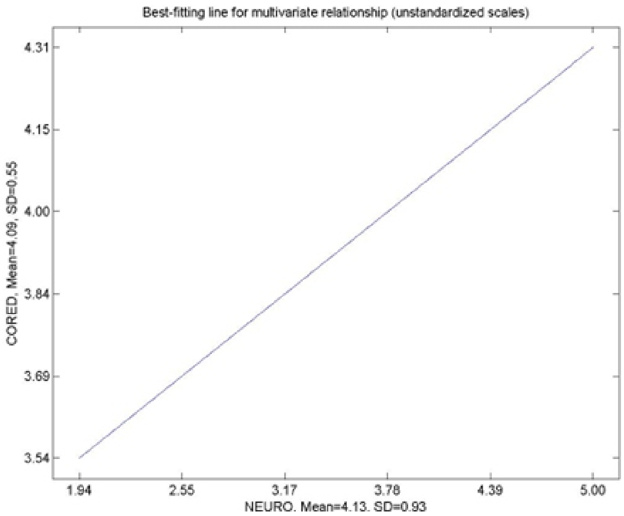

Figure 4: Relationship of NEURO and CORED

Discussion of Results

This study assessed the effect of the 4IR biological driver on construction occupation-related diseases in Northern Nigeria. Two constructs were considered predictor variables, i.e., genome sequencing and neurotechnology, and the outcome variable was construction-occupation-related diseases.

The constructs were identified in previous studies. The predictor constructs were chosen based on the classification of Li *et al*. (2017), who categorized the biological drivers of the 4IR as genome sequencing and neurotechnology. The 4IR was built on the previous revolutions and used biological drivers for the identification and treatment of diseases in the workforce. This is characterized by the fusion of technologies that is clouding the lines between genome sequencing and the neurotechnology spheres, enabling industrial organizations to rapidly diagnose and treat patients.

The results of the measurement model indicate that the research instrument is highly reliable and valid for the intended purpose. Hence, it indicates the reliability and validity of the results.

The findings from this study indicate that the adoption of genome sequencing of the 4IR biological driver had a high effect on construction occupation-related diseases in Northern Nigeria. This result supported the study of Abas *et al*. (2018), which suggested the use of advanced technology and proper observation of the H&S regulatory framework for the construction industry. Similarly, the finding supports that of Biswas, Bhattacharya, and Bhattacharya (2017) on the occupational health status of construction workers, which indicates that construction workers are commonly faced with physical, chemical, biological, mechanical, and psychosocial hazards during their daily working schedules and, as such, suggested the application of sophisticated methods of monitoring the occupational health of workers on sites.

The finding disagrees with the study of Jacky and Chan (2018), which considered the workability of Hong Kong construction workers based on individual and work-related factors. The study concluded that the workability of construction workers was influenced by different lifestyles, physical and psychological demands of their work, job control, and social support. The finding supported the first hypothesis, which stated that there is a significant high effect between the genome sequencing of the 4IR biological driver (GENSE) and the construction of occupation-related diseases in Northern Nigeria.

Moreover, the results of this study further indicated that the neurotechnology of the 4IR biological drivers had a moderate effect on construction occupation-related diseases in Northern Nigeria. This is in line with the findings of Lee, Lin, Seto, and Migliaccio (2017) on the examination and reliability of the use of wearable sensors for monitoring on-duty and off-duty worker physiological status and activities in construction. That result found a very high correlation between the wearable sensors and the medical condition of workers for heart rate, energy expenditure, metabolic equivalents, and sleeping efficiency.

Equally, this study supported that of Liao *et al*. (2022), who explored construction workers' brain connectivity during hazard recognition and found that workers' brain connectivity supplements new evidence underpinning parallel distributed processing theory for workplace hazard recognition.

On the other hand, the results disagree with the results of MacDuffie, Ransom, and Klein (2022) and of Inuwa, Alara & Gambo (2018) because the two studies compared neural device industry representatives and the general public on ethical issues and principles in neurotechnology, which relate to the potential ethical challenges related to agency, identity, privacy, equality, normality, and justice for workers. Therefore, this study supported the second hypothesis, which stated that there is a significant effect between the neurotechnology of 4IR biological drivers and construction occupation-related diseases in Northern Nigeria.

Conclusion

The study assessed the effect of 4IR biological drivers on construction occupation-related diseases in Northern Nigeria, with a view to improving the H&S conditions of the construction workforce on sites. The adoption of the 4IR biological drivers is a valuable tool for improving the H&S of the workforce on the site and improving labour productivity.

The study identified two dimensions of the 4IR biological driver: genome sequencing and neurotechnology. The two (2) dimensions of the biological driver of the 4IR are vital and effective ways of improving the H&S of the workforce. The results indicated that the 4IR biological driver had high and moderate effects on construction occupation-related diseases for genome sequencing and neurotechnology, respectively. It was found that the 4IR biological driver had 60% and 28% effects on genome sequencing and neurotechnology dimensions, respectively. Moreover, the results indicated that about 64% of the predictor variable was explained by the model. Similarly, the two graphs for the relationships between genome sequencing and construction occupation-related diseases and that of neurotechnology and construction occupation-related diseases had straight-line graphs.

The study recommends the adoption of the 4IR biological driver for the management of construction occupation-related diseases on construction sites for the proper transformation of construction sites. Further studies can be carried out to assess the potential of 4IR drivers for the management of the H&S performance of the workforce.

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