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THE IMPACT OF JOB AUTOMATION ON SHIFTS IN LEVELS OF WORK

BY CHANDON BEZUIDENHOUT, ALBERT WÖCKE, NEVILLE PLINT AND MORRIS MTHOMBENI

Gordon Institute of Business Science
University of Pretoria

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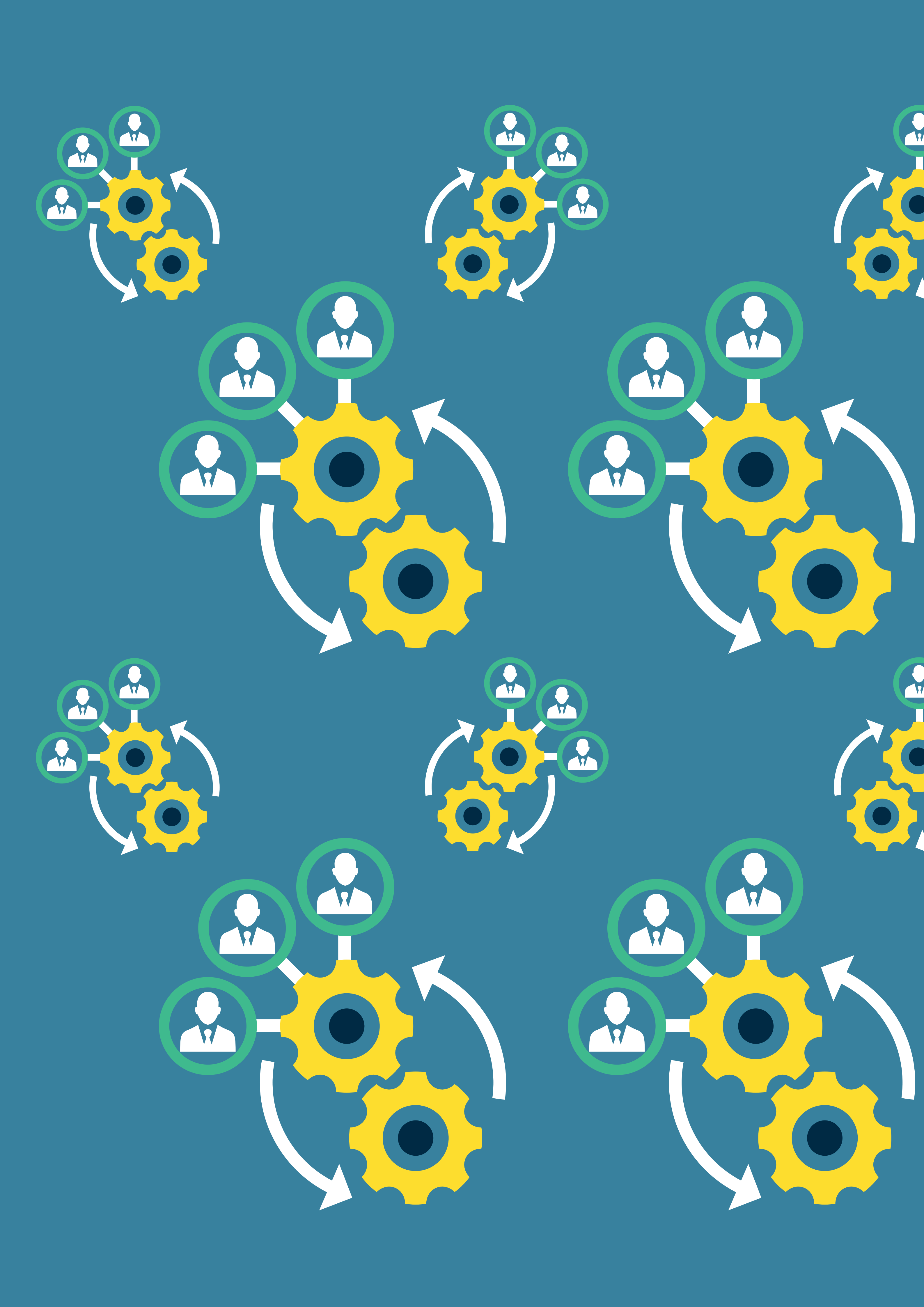

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Contents

Acknowledgements

CHANDON BEZUIDENHOUT

Gordon Institute of Business Science, University of Pretoria
PO Box 787602
Sandton, 2146
South Africa
chandon.bezuidenhout@angloamerican.com

ALBERT WÖCKE

Gordon Institute of Business Science, University of Pretoria
PO Box 787602
Sandton, 2146
South Africa
wockea@gibs.co.za

NEVILLE PLINT

Sustainable Minerals Institute, The University of Queensland
Level 4, Sir James Foots Building (No. 47A)
Corner of College Road and Staff House Road
St Lucia
QLD 4072
Australia
n.plint@uq.edu.au

MORRIS MTHOMBENI

Gordon Institute of Business Science, University of Pretoria
PO Box 787602
Sandton, 2146
South Africa
mthombenim@gibs.co.za

Abstract

The purpose of this research was to determine the impact of technological change on workforce structures and industries. Previous studies forecasted the impact of automation on jobs and categories of jobs, but did not deal with the structure of organisations, particularly levels of work. This study applied Jaques' Stratified Systems Theory model of job analysis to identify occupational groups with higher susceptibility to job automation and project changes in workforce structure for various industries. It was found that automation would shift lower-level tasks to higher strata of work and that it was not possible to generalise the impact of automation across industries, as there would be differences in industries and bureaucracies, which are described here.

Keywords

Automation

Stratified Systems Theory

Jobs

Workforce

1. Introduction

Significant advancement in technologies, such as artificial intelligence, machine learning, robotics, nanotechnology, 3D printing, genetics and biotechnology, has sparked broad debate amongst economists, futurists, and current business leaders regarding the future of jobs (Arntz, Gregory, & Zierahn, 2017; Autor, 2015; Autor, Dorn, & Hanson, 2015; Frey & Osborne, 2017). Various recent publications have predicted broad technological disruption that has the potential to completely displace specific labour, whilst others argue that technological change could bring about more high-quality creative work, promote entrepreneurship, and create greater social freedom (Brynjolfsson & McAfee, 2014; Ford, 2015; Schwab, 2016; Susskind & Susskind, 2015). However, these studies focused on broad labour markets and employment trends, and did not provide perspectives on how organisations and industries would be affected specifically. Knowledge of how organisations are likely to evolve is important for both managers of these organisations and scholars of organisational design. Firms, in particular, need to know the levels of skills and competencies required for the foreseeable future.

2. Theory

2.1. Predicting the future of employment

The first significant modern effort to predict how technology would change the workplace was the skill-biased technological change (SBTC) hypothesis, which is also referred to as the canonical model. The SBTC model was presented in the seminal work of Griliches (1969) and Welch (1970). The basic premise of this model is that technology replaces tasks traditionally performed by unskilled workers and introduces new tasks that demand skilled workers for the effective and efficient implementation of these technologies (Ugur, Churchill, & Solomon, 2017; Ugur & Mitra, 2017; Vivarelli, 2013, 2014, 2015). Accordingly, demand for labour would shift in favour of more skilled workers as the labour market adjusts to the new technologies (Acemoglu & Autor, 2011; Vivarelli, 2014, 2015). However, the SBTC model failed to explain the evolution of inequality and job polarisation observed across several developed economies, such as the United States (US) (Autor & Dorn, 2013; Autor, Katz, & Kearney, 2006, 2008), the United Kingdom (Goos & Manning, 2007), Japan (Ikenaga & Kambayashi, 2016; Jung & Mercenier, 2014), and Europe (Goos, Manning, & Salomons, 2009, 2014; Michaels, Natraj, & Van Reenen, 2014; Spitz-Oener, 2006). The SBTC model also did not account for the rapid diffusion of new technologies that directly substituted capital for labour around tasks performed by moderately skilled workers (Acemoglu & Autor, 2011).

The shortcomings of the SBTC model gave rise to the development of the routine-biased technological change (RBTC) hypothesis (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Beaudry, Green, & Sand, 2016; Cortes, 2016; Goos et al., 2014; Jung & Mercenier, 2014). This model explained the job polarisation effect observed in developed economies when computers were seen complementing non-routine cognitive tasks and substituting routine tasks. The RBTC model classified jobs on the basis of routineness using job task requirements from the *Dictionary of Occupational Titles (DOT)* database and a Routine Task Intensity index (Autor & Dorn, 2013; Autor et al., 2015; Goos et al., 2014).

More recently, Caines, Hoffmann, and Kambourov (2017) argued that classification of tasks based on complexity, as opposed to routineness, provides better insight into occupational wage structures and employment growth. This gave rise to the development of a complex-task biased technological change (CBTC) model. Using the US Department of Labor's Occupational Information Network (O*NET) data, occupations were classified based on the extent to which they relied on complex tasks – that is, tasks that required higher-order skills, such as abstract problem-solving, decision-making, and effective communication. Based on data from 1980 to 2005, this model illustrated that within groups of similar complexity, labour reallocated to non-routine occupations from more routine occupations. Furthermore, it was found that labour reallocated from occupations with lower complexity to occupations with higher complexity. The CBTC model showed that non-routine workers (e.g., low-skill service workers) were not shielded from the effects of technological change, and that the impact of technological change on occupations was largely a function of task complexity (Caines et al., 2017).

Frey and Osborne (2017) used a CBTC approach and adapted a task categorisation model from Autor, Levy, and Murnane (2003) to predict the probability of job automation in the US. Their model predicted that the majority of workers in transportation and logistics, office and administrative support, production, and service occupations were highly susceptible to automation. Moreover, the model predicted that job automation would primarily be confined to low-skilled occupations, whilst high-skilled occupations were found to be relatively resistant to automation. These findings have sparked wide debate amongst economists, policy-makers, futurists, and business leaders about the extent to which technology will displace, modify, or create future jobs (Autor, 2015; Autor & Dorn, 2013; Autor et al., 2015; Frey & Osborne, 2017).

Nevertheless, none of these models could provide sufficient data to predict the shape and form of the future organisation and how jobs would relate to each other in a hierarchy. This perspective is important for managers who will need to predict the levels of skills and configuration thereof in the future, which has been accelerated by the advent of the workplace effects of the COVID-19 pandemic (Donnelly & Johns, 2020). This perspective guides managers and business leaders when they consider broad human resource (HR) strategies, such as organisation restructuring and talent management. In addition, this paper has implications for broader HR management, including training and development, recruitment, retention and remuneration, especially when viewed from a talent management perspective (Van Zyl, Mathafena, & Ras, 2017).

2.2. Stratified systems theory

In 1986, Elliott Jaques published the influential Stratified Systems Theory (SST) that outlined the cognitive processes required for individuals to plan and do goal-directed activities. SST has become one of the most influential approaches in organisational design and is widely used in larger organisations. This applies especially to organisations with complex and stratified hierarchies through which they manage their people resources, because “many hierarchical patterns remain” (Törnblom, Stålne, & Kjellström, 2018, p. 64) in organisations that are further along their digital transformation journey. SST provides a framework for understanding human capability for completing different types of work. It also provides a common classification system for various occupations across different industries. The basic premise of SST is that individuals change to different states of cognitive functioning (shaping, reflective articulation, extrapolation, and transformation) as they reach varying points in cognitive power (measured in time horizons). Jaques (1986, 2006) viewed all work as goal-directed activities bound by quality, time and cost, and exercised within levels of discretion that required judgement and intuition. It was found that the “time span of discretion” – the longest period managers permit subordinates to apply their own discretion in completing a task – was related to work complexity and human capability (Jaques, 1986, 2006; Törnblom et al., 2018). This formed the basis for seven hierarchical strata of increasing complexity of work that required greater abstractive capabilities. Table 1 summarises the seven strata of work, time span of discretion, work complexity, cognitive mechanisms, and typical positions within an organisation.

Classification of occupations based on strata of work combined with a predictive model (e.g., Frey & Osborne, 2017) would provide important insights as to whether technological change is biased towards specific levels within a workforce structure (i.e., Stratum I, II, III, IV or V). Provided there is a significant difference in the probability of job automation of specific strata, “stratum of work” could be introduced into models predicting the impact of automation on the workforce. This could then be used to forecast how organisations would differ across industries.

STRATUM	TIME SPAN	WORK COMPLEXITY	COGNITIVE MECHANISM	POSITION
VII	20 to 50 years	Construct complex systems; construct versus predict future	Linear extrapolation; develop new theories	CEO, super corporation
VI	10 to 20 years	Oversee complex systems; group of business units; plan long term strategy	Reflective articulation between systems; higher conceptual approaches	CEO, international corporation
V	Five to 10 years	Command one complex system; connections to environments	Shape, reshape whole systems, boundaries; utilise theory	Group vice president, international corporation
IV	Two to five years	Oversee operating subsystems; design new methods, policies	Develop alternative systems; abstract from data; parallel processing	General manager; vice president
III	One to two years	Direct one operating subsystem; predict needs 12–18 months out	Linear extrapolation; alternate pathways	Department manager; senior professional
II	Three months to one year	Direct an aggregate of tasks; diagnose problems	Reflective articulation; formulate new ideas; handle ambiguity	First-line manager; supervisor
I	One day to three months	Carry out one task at a time; daily, weekly, monthly quotas	Concrete shaping; concrete thinking; linear pathways	Operators and clerks; day workers

Note: Adapted from Jaques (2006)

Table 1: Characteristics of each stratum of work

3. Methods

This forecasting model was built in three phases: the first phase was to classify occupations according the CBTC approach, the second was to classify the occupations according to the SST model, and then finally classify the occupations according to industry. Industries have different organisational structures due to their technologies and production systems.

3.1. Classification of occupations

This study used a similar CBTC methodology to Autor and Dorn (2013), Caines et al. (2017), and Frey and Osborne (2017). The US Department of Labor's DOT classification system and the 2010 Standard Occupational Classification (SOC) system allowed for the respective data sets to be cross-referenced. The 2010 SOC system classified 840 detailed occupations with similar job duties, skills, education, and training into 461 broad occupations, nine minor occupations, and 23 major groups (U.S. Bureau of Labor Statistics, 2010). This study also used a secondary data set, namely US Occupational Employment Statistics (OES) data, as it contained detailed occupational descriptions and employment statistics per occupation for the US economy, broken down per industry according to the North American Industry Classification System (NAICS). The NAICS is an industry classification system that groups organisations into industries based on similarities in production processes. It uses a six-digit coding system to classify all economic activities in the US across 20 industry sectors and 1 057 detailed industries (U.S. Office of Management and Budget, 2017). Employment data was classified according to the 2010 SOC system, which contained 820 occupations. With the emergence of new roles and the reclassification of the SOC system over the same duration, certain classifications had to be cross-referenced ("crosswalked") to provide comparable figures across different years.

In their studies, Autor and Dorn (2013), Caines et al. (2017), and Frey and Osborne (2017) aggregated the occupations slightly differently. For example, Frey and Osborne (2017) aggregated specific "postsecondary teaching" occupations into a single category and omitted occupations containing "all other", whilst Caines et al. (2017) omitted selected "farm and agricultural" occupations. In total, Frey and Osborne (2017) calculated the probability of job automation for 702 occupations. Autor and Dorn (2013) calculated job routineness for 330 aggregated occupations. Caines et al. (2017) calculated job complexity for 315 aggregated occupations. The approach in this study combined and cross-referenced all of the above-mentioned data sets to produce a total of 291 occupations for the analysis.

In projecting the change in workforce structure from 2016 to 2036, the 2016 OES employment numbers were adjusted for the "probability of job automation" at an occupational level, and aggregated to illustrate the relative change in workforce structure for the entire US economy. The occupations that did not have a corresponding measure of "probability of job automation" were omitted from the analysis. After omissions, this analysis represented 96.3% of the US workforce in 2016.

3.2. Classification of occupations by stratum

The SOC occupations were classified using Jaques' (2006) SST. The 754 occupations were classified as either Stratum I, II, III, IV, or V based on the time span of discretion, task complexity, and cognitive mechanisms required for each occupation. Occupations that comprised completing tasks based on daily, weekly or monthly quotas and involved cognitive mechanisms, such as concrete thinking, concrete shaping and linear pathways, were classified as Stratum I. Typical examples included operators, clerks, cleaners, assistants, and helpers. Occupations that involved the directing of aggregated tasks and diagnosis of problems through cognitive mechanisms, such as reflective articulation, were classified as Stratum II occupations. Typical examples comprised supervisors and specialist roles like nurses, pilots, and technicians. Occupations that involved directing operating subsystems through cognitive mechanisms of linear extrapolation were classified as Stratum III occupations. Typical examples were professional and management occupations, such as engineers, doctors, lawyers, and managers. Occupations that involved overseeing operating subsystems and designing new methods and policies through cognitive mechanisms of abstracting and parallel processing were classified as Stratum IV, an example of which was general managers. Lastly, occupations that involved the commanding of a complex subsystem through cognitive mechanisms, such as shaping, were classified as Stratum V – for instance, chief executive officers (CEOs). Jaques' model includes additional strata, but this study did not include those as they were more appropriate for corporations and coordinating structures. This study did not expect automation to greatly influence those roles in the medium term.

3.3. Workforce structure and industry classification

To illustrate the change in workforce structure at an industry level, a measure for workforce structure was introduced. A similar approach to Tåg, Åstebro, and Thompson (2016) was used to describe span of control for different hierarchies within firms to determine the ratio of Stratum I, II, III, and IV occupations relative to the number of Stratum V occupations within an industry. This approach utilised the US OES data from 1999 to 2016, which includes detailed employment statistics per occupation and industry. This metric was used to illustrate the relative workforce structure distributions for different industries, which could be classified into four main types based on their workforce ratios. The 2016 workforce structure distributions were used to classify the 20 US industries as either Type 1, 2, 3, or 4 industries. Type 1 industries are characterised as divisionalised forms with large middle lines and small technostructures (Mintzberg, 1980). Type 2 industries are characterised as machine bureaucracies with a large technostructure and high division of labour through vertical and horizontal job specialisation (Mintzberg, 1980). In both these cases, a large portion of Stratum I occupations is projected to be substituted by technology. Other industry types, such as Types 3 and 4, resemble professional bureaucracies and adhocracies (Mintzberg, 1980).

The industry types were determined as follows:

i. Type 1 industries were characterised by a pyramid-like workforce structure where the largest complement of workers was Stratum I.

ii. Type 2 industries were characterised by a large complement of Stratum I occupations, but the Stratum III complement was either larger or equal to the Stratum II complement.

iii. Type 3 industries were characterised by a workforce structure where the largest complement was Stratum II occupations.

iv. Type 4 industries were characterised by a workforce structure where the largest complement was Stratum III occupations.

A summary of the four industry types, generic workforce structures, and typical workforce ratios is given in Figure 1

3.4. Data analysis

The change in employment for each industry was projected by calculating the percentage change in employment within each industry for Stratas I to III from 2016 to 2036 using the model by Frey and Osborne (2017). Changes in Stratum IV and V occupations were not considered, as these occupations were not industry-specific.

Frey and Osborne's (2017) methodology used machine learning experts at Oxford University Engineering Sciences Department to evaluate the possibility of automating occupations listed on the O*NET database of occupations. The O*NET database is the most complete and comprehensive database of job descriptions and is therefore widely accepted for studies like this one. Frey and Osborne (2017) then used this process to develop an algorithm and formula for classifying jobs as more or less vulnerable to automation. The algorithm considers task complexity, task routineness, and finger ambidexterity.

This study used multiple regression to analyse data, which was consistent with the approaches of other scholars who examined related questions. For example, Autor and Dorn (2013) and Caines et al. (2017) applied regression analysis to model the relationship between task routineness and complexity, respectively, and wages as the dependent variable. Moreover, multiple regression was appropriate in this case as the dependent variable was a continuous variable and two or more variables were continuous or nominal variables. "Probability of job automation" was the dependent variable and was measured on a scale of 0 to 1. Routineness and complexity were also continuous variables.

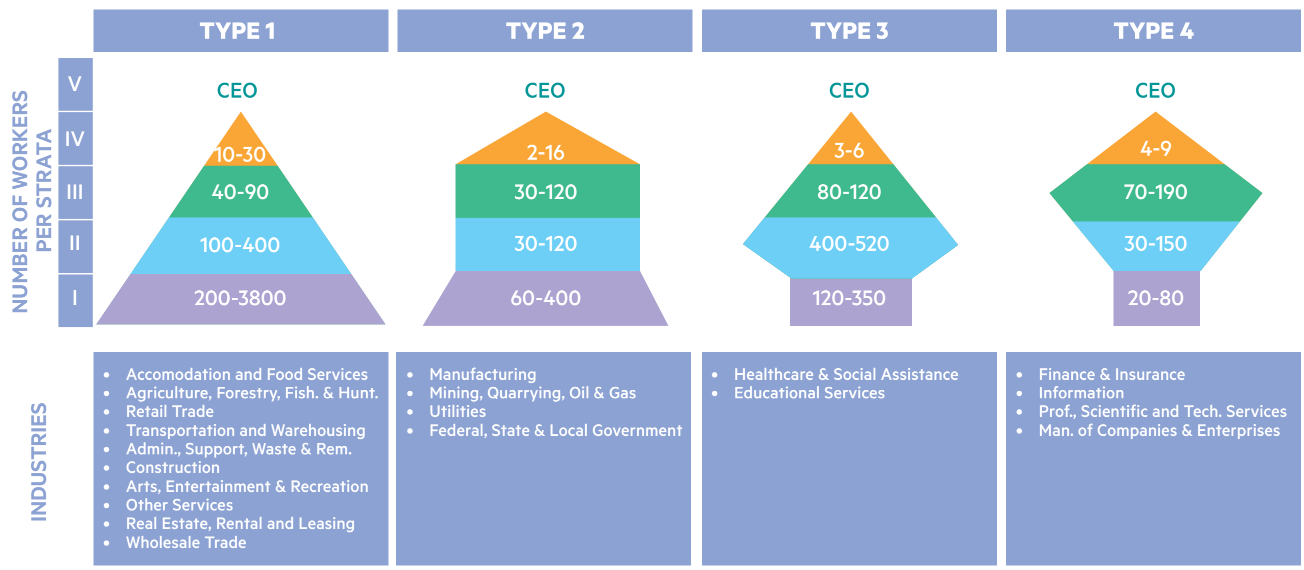


Figure 1: Workforce structures for Type 1–4 industries

4. Discussion

This forecasting model was built in three phases: the first phase was to classify occupations according the CBTC approach, the second was to classify the occupations according to the SST model, and then finally classify the occupations according to industry. Industries have different organisational structures due to their technologies and production systems.

4.1. Probability of job automation per stratum

Statistically significant differences were found in the probability of job automation between Stratum I, II, and III occupations. Stratum I occupations had the highest probability for job automation. The probabilities of job automation were significantly lower for Stratum II and III occupations. The data sets for Stratum IV and V occupations consisted of a single data point. A summary of the probabilities of job automation of each stratum of work is given in Figure 2.

Based on this analysis, it is evident that job automation is biased towards displacing Stratum I (median = 0.830) occupations. Stratum II occupations (median = 0.175) were less susceptible to automation than Stratum I occupations. Stratum III occupations (median = 0.039) were less susceptible to automation than both Stratum I and II occupations. Since Stratum IV and V occupations only comprised a single data point each, no statistical conclusion could be drawn regarding the susceptibility of automation of these groups relative to Stratum I, II, and III occupations. However, based on the relative probability of job automation for "general and operations managers" and "chief executives", there is sufficient evidence to suggest that Stratum IV occupations were more susceptible to automation than Stratum V occupations.

Thereafter, a multiple linear regression analysis was conducted to establish how much of the variation in the probability of job automation (dependent variable) was explained by the independent variables of "routineness", "complexity", and "stratum". This was done through two models. Regression Model 1 examined the probability of job automation and measures of task routineness and task complexity. Regression Model 2 added "Stratum of work" to explain how much of the variation in "probability of job automation" was due to the independent variables of routines, complexity, and stratum for the occupations. The regression equation based on this analysis was:

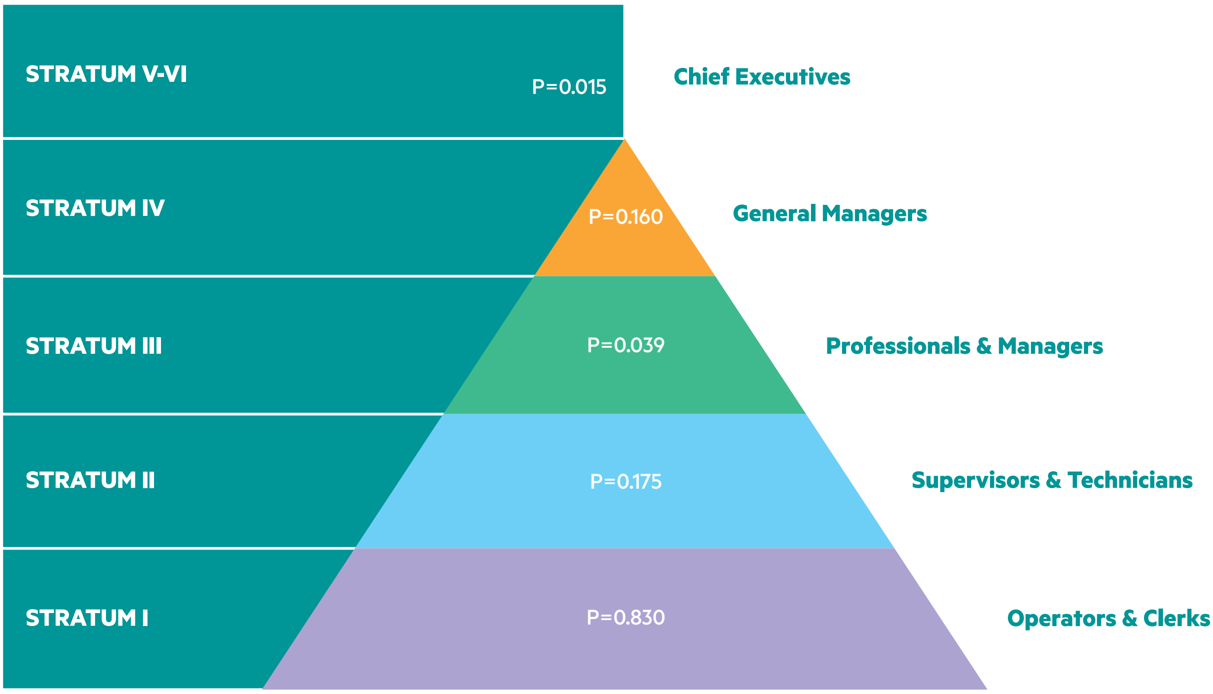


Figure 2: Summary of the probabilities of job automation of Stratum I, II, III, IV, and V occupations

P(Automation) = 0.841 + 0.315(Routineness) - 0.433(Complexity) - 0.140(Stratum)

The coefficient for complexity in this model is -0.433 (-0.284 to -0.582, 95% CI). Thus, an increase of 10% in task complexity would decrease the probability of job automation by 4.33% (2.84% to 5.82%, 95% CI). The coefficient for routineness is 0.315 (0.239 to 0.442, 95% CI). Consequently, an increase of 10% in routineness would increase the probability of job automation by 3.15% (2.17% to 4.13%, 95% CI). The coefficient for stratum is -0.140 (-0.087 to 0.193, 95% CI). Hence, an increase in stratum resulted in a lower probability of job automation. A summary of the results from the multiple regression analysis is provided in Table 2.

INDEPENDENT VARIABLE	REGRESSION MODEL 1			REGRESSION MODEL 2		
	B	SEB	Beta	B	SEB	Beta
Constant	0.752	0.045		0.841	0.046	
Routineness	0.341	0.052	0.275*	0.315	0.050	0.254*
Complexity	-0.736	0.051	-0.606*	-0.433	0.076	-0.356*
Stratum				-0.140	0.027	-0.323*
N	291			291		

*Notes: * p < 0.05; B = unstandardised regression coefficient; SEB = Standard error of the coefficient; Beta = standardised coefficient*

Table 2: Summary of multiple regression analysis for Regression Models 1 and 2

The workforce structure for the US economy in 2036 is forecast to be significantly different to that of 2016. The proportion of Stratum I occupations in the US economy is projected to reduce from 54% in 2016 to 27% in 2036. This significant reduction would be offset by increases in the relative proportion of all other strata of work. These are as follows:

i. The proportion of Stratum II occupations will increase from 28.2% to 41.2%.

ii. The proportion of Stratum III occupations will increase from 16.0% to 28.2%.

iii. The proportion of Stratum IV occupations will increase from 1.6% to 3.2%.

iv. The proportion of Stratum V occupations will increase from 0.2% to 0.4%

This is consistent within strata role changes occasioned by disruptive macro changes (Barley & Kunda, 2001; Grant & Parker, 2009). Moreover, it is consistent with evidence of increased job insecurity for those historically displaced in lower strata, which is also attended with their prolonged unemployment (Kalleberg, 2009). This highlights the importance of understanding by scholars and managers of the trajectory of job role changes occasioned by disruptive macro-economic changes.

4.2. Workforce ratios per industry and automation

Workforce ratios were calculated by determining the ratio of Stratum I, II, III, and IV occupations relative to Stratum V occupations, and 2016 was compared to 2036 forecasts. Tables 3 and 4 summarise the workforce ratios for each industry in 2016 and 2036 (projected), respectively.

INDUSTRY SECTOR	I:V RATIO	II:V RATIO	III:V RATIO	IV:V RATIO	V:V RATIO
Agriculture, Forestry, Fishing and Hunting	1 796	125	36	17	1
Mining, Quarrying, Oil and Gas Extraction	393	97	101	16	1
Utilities	225	121	116	11	1
Construction	512	96	56	15	1
Manufacturing	378	74	84	10	1
Wholesale Trade	191	147	51	13	1
Retail Trade	1 786	415	78	39	1
Transportation and Warehousing	1 250	201	67	18	1
Information	72	148	162	8	1
Finance and Insurance	79	120	123	7	1
Real Estate, Rental and Leasing	273	114	74	13	1
Professional, Scientific, Technical Services	47	95	185	9	1
Management of Companies and Enterprises	19	31	63	4	1
Administrative, Support, Waste Management and Remediation Services	586	192	77	14	1
Educational Services	151	521	80	3	1
Healthcare and Social Assistance	363	411	120	6	1
Arts, Entertainment, and Recreation	391	117	41	12	1
Accommodation and Food Services	3 737	318	91	32	1
Other Services	285	77	52	11	1
Federal, State, and Local Government	55	35	29	2	1

Table 3: Workforce ratios per industry in 2016

INDUSTRY SECTOR	I:V RATIO	II:V RATIO	III:V RATIO	IV:V RATIO	V:V RATIO
Agriculture, Forestry, Fishing and Hunting	1 386	52	26	15	1
Mining, Quarrying, Oil and Gas Extraction	102	56	71	13	1
Utilities	94	71	93	9	1
Construction	154	62	40	13	1
Manufacturing	75	45	69	8	1
Wholesale Trade	42	57	37	11	1
Retail Trade	269	237	63	34	1
Transportation and Warehousing	292	124	44	15	1
Information	13	95	130	7	1
Finance and Insurance	5	59	65	6	1
Real Estate, Rental and Leasing	59	42	28	11	1
Professional, Scientific, Technical Services	7	40	143	8	1
Management of Companies and Enterprises	4	14	46	4	1
Administrative, Support, Waste Management and Remediation Services	145	95	56	12	1
Educational Services	41	451	68	3	1
Healthcare and Social Assistance	194	302	111	5	1
Arts, Entertainment, and Recreation	120	77	31	10	1
Accommodation and Food Services	446	130	79	27	1
Other Services	109	46	40	10	1
Federal, State, and Local Government	25	24	22	1	1

Table 4: Workforce ratios per industry in 2036 (projected)

The above-mentioned workforce ratios were used to construct workforce structure distributions for each industry. Workforce structures were then categorised into the four industry types and percentage changes of the strata calculated. These are illustrated in Table 5.

CLUSTER & MECH.		INDUSTRY	CHANGE, EMPLOYMENT (%)	STRATUM I CHANGE (%)	STRATUM II CHANGE (%)	STRATUM III CHANGE (%)
HIGH	A	Retail Trade	-74.4%	-32.5%	21.4%	7.1%
		Transportation and Warehousing	-69.5%	-20.1%	13.1%	4.8%
		Arts, Entertainment, and Recreation	-58.1%	-19.2%	11.2%	5.7%
	B	Manufacturing	-64.2%	-31.2%	9.0%	19.4%
		Wholesale Trade	-64.0%	-18.9%	2.0%	12.1%
	C	Accommodation and Food Services	-83.9%	-24.1%	11.4%	9.4%
		Mining, Quarrying, Oil and Gas Extraction	-60.5%	-22.7%	7.1%	12.5%
		Finance and Insurance	-59.6%	-20.5%	7.2%	10.7%
		Admin, Support, Waste Management and Remediation Services	-65.0%	-20.4%	8.7%	9.3%
		Construction	-61.0%	-18.2%	8.8%	6.6%
		Real Estate, Rental and Leasing	-70.6%	-15.6%	5.5%	4.5%
		Other Services	-52.6%	-13.8%	4.1%	7.5%
LOW	A	Educational Services	-26.6%	-12.7%	11.1%	1.5%
	B	Utilities	-44.2%	-12.4%	1.0%	10.1%
		Information	-37.7%	-13.1%	0.9%	11.3%
	C	Federal, State, and Local Government	-40.5%	-10.2%	3.6%	5.6%
		Healthcare and Social Assistance	-33.0%	-8.6%	3.6%	4.8%
	D	Management of Companies and Enterprises	-43.1%	-10.4%	-5.9%	13.8%
		Professional, Scientific, and Technical Services	-41.9%	-10.3%	-7.9%	16.8%
	E	Agriculture, Forestry, Fishing and Hunting	-26.1%	2.7%	-2.8%	0.0%

Table 5: Classification of the US industries based on the projected change of employment and mechanism of workforce structure adjustment

The results indicate two industry clusters: industries with a greater than 50% (high) projected change in employment, and industries with a less than 50% (low) projected change in employment. The projected change in employment for industries in the high cluster ranged from 53% to 84% and consisted of the following 12 industries: Retail Trade; Manufacturing; Accommodation and Food Services; Mining, Quarrying, Oil and Gas Extraction; Finance and Insurance; Administrative, Support, Waste Management and Remedial Services; Transportation and Logistics; Arts, Entertainment, and Recreation; Wholesale Trade; Construction; Real Estate, Rental and Leasing; and Other Services.

The projected change in employment for industries in the low cluster ranged from 26% to 44%. This cluster consisted of the following eight industries: Utilities; Management of Companies and Enterprises; Professional, Scientific, and Technical Services; Federal, State, and Local Government; Information; Healthcare and Social Assistance; Educational Services; and Agriculture, Forestry, Fishing and Hunting.

4.2.1. Type 1 industries

Type 1 industries were characterised by a workforce structure in a typical pyramid configuration, with its largest complement being Stratum I occupations. That is, for every CEO within this industry, there were 10–30 general managers, 40–90 professionals, 100–400 supervisors, and 200–3 800 operators or clerks. The workforce structures of these industries closely represent a divisionalised form. The key coordinating mechanism for organisations within these industries is the standardisation of outputs (Mintzberg, 1980). Thus, these organisations generally have large middle lines (e.g., supervisors and managers) and smaller technostructures (e.g., analysts and professionals). The division of labour is high, leading to vertical and horizontal job specialisation, which results in a large bureaucratic pyramid-like workforce structure with a large complement of Stratum I occupations. With the exception of the Agriculture, Forestry, Fishing and Hunting industry, Type 1 industries are likely to have Stratum I jobs absorbed by Stratum II and Stratum III workers due to automation. Agriculture, Forestry, Fishing and Hunting are likely to experience a reduction in Stratum II jobs and a growth in Stratum I jobs.

4.2.2. Type 2 industries

Type 2 industries were characterised by a workforce structure where the largest complement was Stratum I occupations, but the complement of Stratum III occupations was either larger or equal to the Stratum II complement. That is, for every CEO within this industry, there were 2–16 general managers, 30–120 professionals, 30–120 supervisors, and 60–400 operators or clerks. The workforce structures of these industries closely represent machine bureaucracies. The key coordination mechanism for organisations within these industries is the standardisation of work (Mintzberg, 1980). Thus, these organisations generally have large technostructures consisting of analysts, planners, and professionals, which are classified as Stratum II and III occupations. The division of labour is high, leading to vertical and horizontal job specialisation. Hence, the organisation has a large complement of Stratum I occupations. The impact of technological change on Type 2 industries ranges from moderate to high. The Manufacturing, and Mining, Quarrying, Oil and Gas industries will be severely impacted, whilst the Utilities and Federal, State and Local Government industries will be moderately affected. Due to the high complement of Stratum II and III occupations, the reduction in Stratum I occupations occurs through changes in Stratum II jobs replacing Stratum I roles and, to a lesser extent, Stratum III jobs assuming Stratum I jobs.

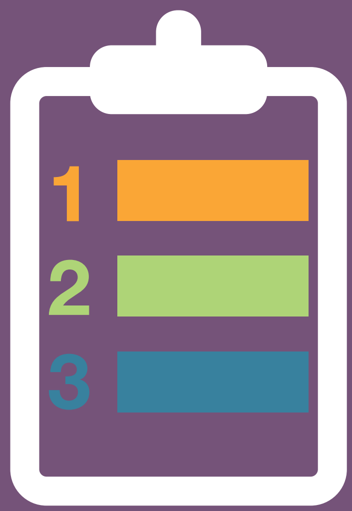
4.2.3. Type 3 industries

Type 3 industries were characterised by a workforce structure comprising the largest complement of Stratum II occupations. That is, for every CEO within this industry, there were 3–6 general managers, 80–120 professionals, 400–520 supervisors, and 150–350 operators or clerks. The workforce structures of these industries closely represent professional bureaucracies. The key coordination mechanism for organisations within these industries is the standardisation of skills (Mintzberg, 1980). Consequently, these organisations have a large complement of skilled professionals (Stratum II and III occupations) in the operating core, together with a large complement of support staff who perform simple routine tasks (Stratum I and II occupations). Horizontal job specialisation is high, whilst vertical specialisation is low. Therefore, the organisation has a large complement of Stratum II and III occupations, with a smaller complement of Stratum I occupations. The impact of technological change on Type 3 industries is low, but Stratum I jobs will be absorbed primarily by Stratum III and, to a lesser extent, Stratum II workers.

4.2.4. Type 4 industries

Type 4 industries were characterised by a workforce structure where the largest complement was Stratum III occupations. That is, for every CEO within this industry, there were 4–9 general managers, 70–190 professionals, 30–150 supervisors, and 20–80 operators or clerks. The workforce structures of these industries closely represent adhocracies. The key coordination mechanism for organisations within these industries is mutual adjustment (Mintzberg, 1980). Thus, these organisations have a large complement of skilled professionals (Stratum III occupations) who work in multidisciplinary specialist teams. These teams are supported by a smaller complement of support staff (Stratum I and II occupations). Horizontal job specialisation is high, whilst vertical specialisation is low. The impact of technological change on Type 4 industries is low, except in the case of the Finance and Insurance industry, where Stratum I and II jobs are going to be taken over by Stratum III workers.

5. Conclusion



While this analysis provides a good view of what the organisational structures will be in the US in 2036, it does not predict which new industries and associated jobs will be created over this period. Firstly, this study's scenario assumes that the US economy can facilitate the required growth in professional occupations without being constrained by the requirements for a minimum number of unskilled occupations. Secondly, it assumes that workers, at an aggregated level (e.g., across the US economy), have the capability to shift from unskilled to professional occupations and that they have access to suitable education or experience. Thirdly, it assumes that technological change and automation of unskilled occupations take place linearly over time. It must be understood that this has implications for economies with different labour market structures to that of the US, but this study's view is that industries using similar technologies tend to adopt similar methods of organisation. This is already evident with the rapid adoption of bots in the financial services industries in South Africa (Breidbach, Keating, & Lim, 2019; Ndemo & Weiss, 2017). A further discussion on the adoption of automation is available in the Jobs of Tomorrow study by the World Economic Forum (2020).

In emerging markets, it cannot be assumed that the workforce would have the skills or access to opportunities to adapt their abilities in response to automation. In the South African context, the disruption is even greater, particularly with high unemployment levels amongst lesser-skilled people. Jaques' model is premised on a match between the skills and competencies of the employee and the required job. Emerging markets are characterised by a surplus of lower-skilled jobseekers and a scarcity of higher-skilled employees. As automation becomes more accessible for firms to implement, lesser-skilled employees who do not have the competence to upgrade their skills will be most affected. Similarly, jobseekers who do not have the skills or opportunities to develop the appropriate skills and exposure to automation will not find employment. Stratum II jobs will be the entry-level jobs, but these jobs will co-exist with technology and automation. This has enormous implications for emerging countries like South Africa. At a policy level, the implications for the education system and industrial policy are quite clear. At a firm level, the implications are that HR will be under pressure to manage the social consequences of displaced Stratum I employs and to attract and retain those able to engage with technology from Stratum II above, despite a small pool of specialist skills.

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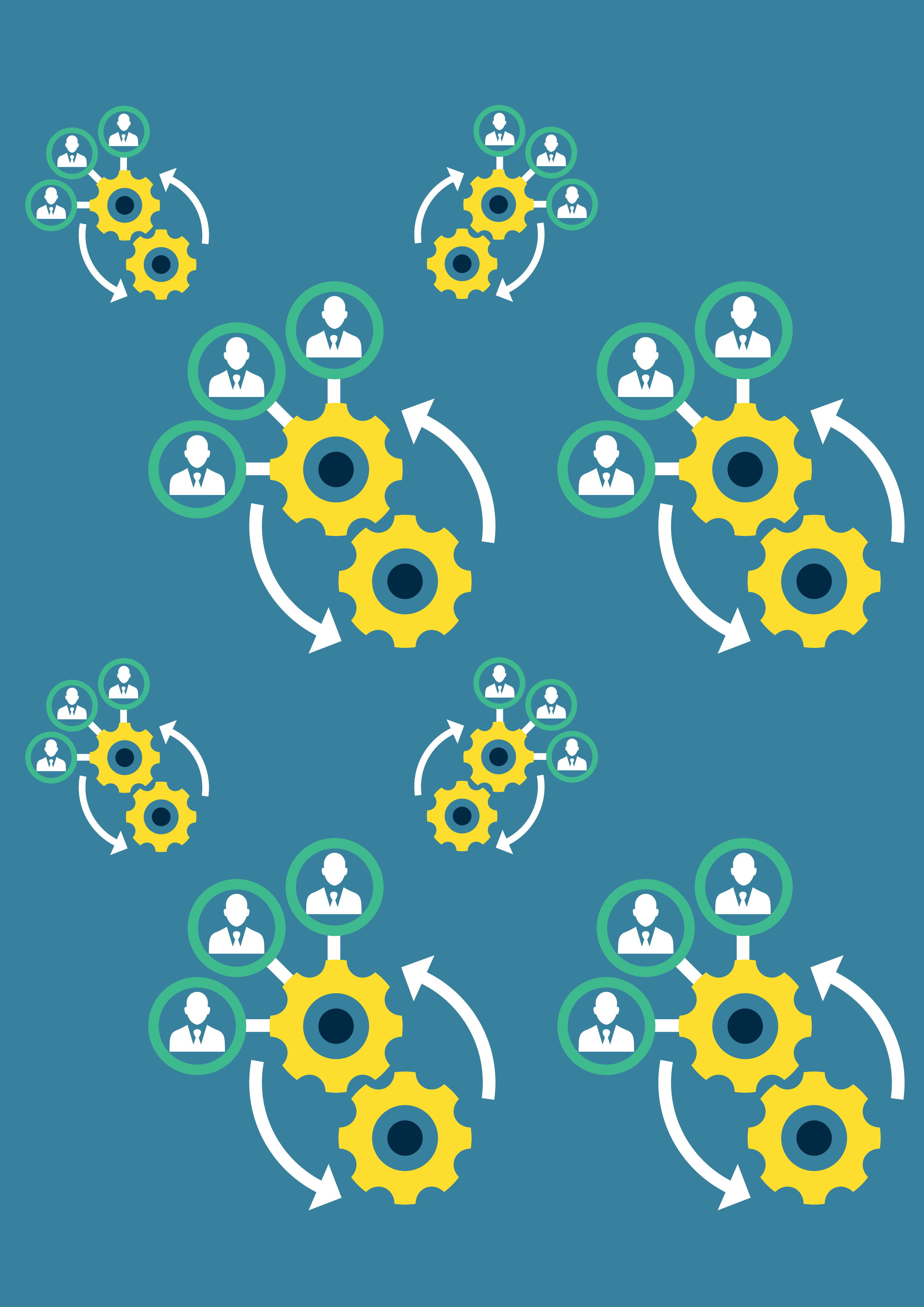

Gordon Institute
of Business Science
University of Pretoria

26 Melville Road, Illovo, Johannesburg
P O Box 787602, Sandton, South Africa, 2146
011 771 4000 | Acumen@gibs.co.za