

Digitalization and the Future of Employment: A Case Study on the Canadian Offshore Oil and Gas Drilling Occupations

Thumeera R. Wanasinghe¹, Member, IEEE, Raymond G. Gosine², Bui K. Petersen³, and Peter J. Warrian⁴

Abstract—This paper presents a novel approach to identifying reskilling requirements, job merging pathways, and a tentative timeline for transforming offshore oil and gas drilling occupations amid the fourth industrial revolution (Industry 4.0). The proposed algorithm focuses on potential job merging due to technological adoption. It introduces a scaling factor named *digital readiness level* to incorporate modulation factors (e.g., cost of development and deployment of new technologies, labour market dynamics, economic benefits, regulatory readiness, and social acceptance) that act as catalysts or hindrances for technology adoption. A feature-based approach is developed to assess the similarities between occupations, while a mathematical model is developed to project automation trajectories for each job under investigation. These facilitate the consideration of potential job merging scenarios and the associated timeline. Since technology adoption depends on the industry, region, occupation, and stakeholder's ability to manage the transformation, the proposed algorithm is presented as a case study on Canadian offshore oil and gas drilling occupations. However, this algorithm and approach can be applied to other industries or occupation structures. The proposed algorithm projects that the total number of personnel on board (POB) in a typical offshore drilling platform will be reduced to six by 2058. A sensitivity analysis was conducted to assess the robustness of the proposed algorithm against variations in the feature values and weighting factors. It was found that when changing feature values and weighting factors up to $\pm 20\%$ of their original values, only one job that remains after 2058 follows three different job merging pathways, while others remain unchanged. Even the job that followed three different pathways was composed of the same source jobs compared to the corresponding job in the baseline results.

Note to Practitioners—This research is inspired by the ongoing digital transformation initiatives and their socioeconomic impact.

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Thumeera R. Wanasinghe is with the Faculty of Engineering and Applied Science, Memorial University of Newfoundland, St. John's, NL A1B 3X7, Canada (e-mail: ruwansiriwat@gmail.com).

Raymond G. Gosine is with the Faculty of Engineering and Applied Science, Memorial University of Newfoundland, St. John's, NL A1B 3X7, Canada, and also with the Innovation Policy Laboratory, Munk School of Global Affairs and Public Policy, University of Toronto, Toronto, ON M5S 3K7, Canada.

Bui K. Petersen is with the Sobey School of Business, Saint Mary's University, Halifax, NS B3H 3C2, Canada.

Peter J. Warrian is with the Innovation Policy Laboratory, Munk School of Global Affairs, University of Toronto, Toronto, ON M5S 3K7, Canada.

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The adoption of digital technologies, such as automation, robotization, digital twins, data-driven decision-making systems, smart devices, and cloud computing technologies, gradually transform existing workplaces into digitally-enabled smart workplaces. Therefore, stakeholders must invest in training programs to reskill existing workforces and to orient prospective employees to work at these smart workplaces. If technology adoption occurs at a rapid or slower pace than workforce reformation, industries cannot gain the optimum benefit from their digital transformation initiatives. Also, human capital investments may not generate much benefit if technology adoption and workforce reformation occur at different rates. Therefore, this work presents a novel framework to predict future employment scenarios, particularly for the workers in offshore oil and gas drilling activities, along with a tentative timeline. Stakeholders can utilize the proposed framework to effectively plan the pace of technological adoption, future workforce transformation and human capital investments.

Index Terms—Automation, job merging, future of work, technological unemployment, reskilling, digital readiness (DR).

I. INTRODUCTION

AMID the fourth industrial revolution (Industry 4.0), many industries have been adopting digital technologies, including automation, robotization, digital twins, data-driven decision-making systems, smart sensors/devices, advanced visualizing technologies and cloud computing technologies, to improve the safety and efficiency of industrial operations. In addition to benefiting employees, such technologies can help industry respond to demographic challenges, such as the big crew change and the mismatch between labour supply and demand. Such technology adoption has been transforming existing workplaces into digitally-enabled smart workplaces filled with more machinery. It is anticipated that such technology adoption will result in the displacement of some jobs, creation of new job, reshaped skill profiles for existing jobs, and altered ways of working [1], [2]. Therefore, it is important to prepare both the existing and prospective workforce to minimize the negative socioeconomic impact of technology adoption and to enhance the economic benefits. It is possible to implement immersive training environments to train employees [2], [3], [4], [5]. Such training can be supplemented by human-machine interfaces (HMIs) that adapt to operators' skills and capabilities [1], [6], [7], [8], [9]. However, designing and implementing new education programs, immersive workplace training systems, and adaptive HMIs require enormous effort and investment.

When employee reskilling activities occur at a different rate than technology adoption, stakeholders will not gain the expected results from their digital transformation initiatives. Therefore, it is important to understand the susceptibility of existing jobs to digital transformation, particularly for automation and robotization, and to plan employee reskilling activities effectively. To support this objective, numerous studies have been performed to predict susceptibilities of existing jobs to automation [10], [11], [11], [12], [13], [14], [15], [16].

Although all these studies predict the level of automation in the future workforce and potential emerging and declining jobs, they do not present possible job merging scenarios arising from task automation and they do not present a timeline for the transformation. Additionally, the studies related to the socioeconomic impact of technology adoption are polarized between two theses: (1) technology adoption increases global unemployment level and (2) technology adoption expands the job market, creating more opportunities [17], [18], [19], [20], [21], [22], [23], [24]. The rationale for these two distinct observations is that technology adoption depends on the industry, region, occupation, and stakeholder's ability to manage the transformation. Therefore, employment transformation should be considered within an industry, a geographical region or an occupation-specific case study, rather than as a general thesis.

Since the existing literature does not present possible job merging scenarios nor a tentative timeline for transformation, but rather attempts to develop a general conclusion about technological unemployment/employment, it is challenging to use existing studies directly to predict the future employment scenarios and reskilling requirements with a tentative timeline. The research presented in this article, therefore, proposes a framework to utilize the existing literature to predict future job merging scenarios and timeline, with employment within offshore oil and gas drilling occupations used to illustrate and validate the approach. Offshore oil and gas drilling operations currently involve a workforce representing approximately 40 different occupations with distinct Canadian NOC codes. The overall objective of the workers associated with an operation is to drill oil and gas wells from an offshore oil and gas platform. Jobs tend to be a combination of tasks that are done manually or utilizing technology and the workers tend to be co-located geographically. As technology advances, the mix of manual and technology-mediated tasks changes which gives rise to opportunities for workers to take on activities from other occupations on the platform.

The study develops a reskilling cost matrix, job merging pathways matrix, potential job automation, integrations and creations, and the tentative timeline. The proposed career pathway calculation approach is validated through a case study wherein the offshore drilling occupation structure is used as a target occupation group for the study. Stakeholders can utilize the results of this study to more effectively plan their technology adoption rate, their future workforce transformation and their investment in human capital for reskilling. Although the job merging framework is developed for Canadian offshore oil and gas drilling occupations,

it can directly be applied to other industries or occupational structures. The proposed algorithm projects that the total number of personnel on board (POB) in a typical offshore drilling platform will be reduced to six by 2058. A sensitivity analysis was conducted to assess the robustness of the proposed algorithm against variations in the feature values and weighting factors. It was found that when changing feature values and weighting factors up to $\pm 20\%$ of their original values, only one job that remains after 2058 follows three different job merging pathways, while others remain unchanged. Even the job that followed three different pathways was composed of the same source jobs compared to the corresponding job in the baseline results.

The structure of the article is as follows. Section II summarizes the existing literature in the area of technological automation of the workforce. Section III presents the proposed job merging framework. The simulation study and the results are presented in Section IV. Finally, Section V summarizes the overall findings of this study.

II. BACKGROUND

Several studies analyzed the susceptibility of existing jobs to automation and computerization. Work presented in [11] and [11] adapted the task categorization model from [10] and developed occupation-based approach to predict the susceptibility of existing jobs for automation. This occupation-level modelling indicates mass unemployment implications (e.g., approximately 47% of US employment has a high probability (>0.7) of being automated during the next two decades), which is expected to be an overestimation for the impact of automation on the workforce. Work presented in [12], [14], [25], [15], and [16] used task-based approaches to predict the susceptibility of existing jobs for automation. A study by McKinsey Global Institute evaluated the technical automation potential of over 2000 work activities [15]. This study concluded that 50% of activities across all occupations could be automated by exploiting existing demonstrated technologies. The work presented in [13] transferred the findings of [11] and [25] into the Canadian labour market context. Although all of these studies predict the level of automation in the future workforce, as well as emerging and declining jobs, the results do not present possible job merging scenarios arising in parallel with task automation.

The impact of technology adoption on the workforce depends on the tasks associated with individual occupations [26]. Since skills characterize tasks, the relationships between technologies and skills can be used for modelling the impact of technological adoption [27]. Using existing labour market data, such as the O*NET database of the US labour market, mathematical models have been developed to interpret the dynamics in employment and wage shifts over time in response to technology adoption. Among the available models, the skill-biased technological change model (SBTC), the routine-biased technological change model (RBTC) and the complex-task biased technological change (CBTC) model are considered as the primary technological change models [28]. The SBTC model assumes that the

tasks traditionally performed by unskilled workers will be replaced by machines, demanding skilled workers to operate these advanced machines [29], [30], [31]. The RBTC model, which classifies the tasks into three main categories, namely abstract tasks, routine tasks and non-routine tasks, shows that technological adoption reduces the labour demand for routine tasks while increasing the labour demand for non-routine and abstract tasks [10], [26], [32]. The CBTC model classifies tasks based on complexity instead of routineness to interpret the changes in occupational wage structures and dynamics in employment [28].

Industrial firms have been automating and robotizing their workplaces over several decades. The COVID-19 increased the rate of automation, robotization, remote operations, and digitalization [33], [34], [35]. According to [33], 100 million workers in China, France, Germany, India, Japan, Spain, the United Kingdom, and the United States may need to change occupations by 2030. The work presented in [34] made four projections for the post-COVID-19 economy. These predictions include increasing telework, city de-densification, large-firm consolidation, and forced automation, affecting low-wage workers and creating economic inequality across the existing workforce. As reported in [35], females in mid-to-low-wage jobs and lower education levels were severely affected during COVID-19. This worker group had a more significant initial decline in employment during the COVID-19 pandemic and will likely have a weaker post-pandemic recovery. Therefore, business leaders and policymakers are required to invest in digital infrastructure, in reskilling workers, and in innovative worker benefits and support mechanisms to assist and prepare the existing and future workers to be able to function in a rapidly changing industrial ecosystem [33].

III. METHODOLOGY

Since technology adoption depends on the industry, region, occupation, and stakeholder's ability to manage the transformation, the proposed job merging algorithm is presented as a case study.

A. Target Occupation Group for the Case Study

The oil and gas (O&G) industry is a high-risk and capital-intensive business that is heavily regulated to minimize health, safety and environmental risks. There could be severe consequences if accidents occur during drilling, production, processing, or at a storage facility. According to the Worldwide Offshore Accident Databank (WOAD), there were 2288 fatalities distributed among the 6451 offshore accidents between 1970 and 2012 [36]. Accidents can also pose environmental risks. Among the offshore oil and gas related operations, offshore drilling is considered to be a challenging and risky activity. For example, the explosion that occurred on the Deepwater Horizon platform, a semi-submersible, mobile, floating, dynamic positioning drilling rig, is the largest marine oil spill in the history of the petroleum industry. The accident also contributed to the loss of lives of 11 personnel [37].

Automation and robotization can be deployed to improve the reliability and safety of offshore drilling operations

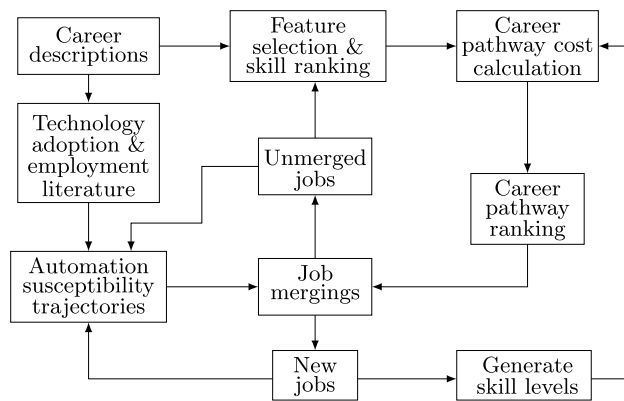


Fig. 1. Overview of the proposed career pathways and job merging framework.

while minimizing the number of personnel onboard. Current digital initiatives by the offshore oil and gas industry aim to remove (or reduce the number of) humans working in hazardous environments, such as drilling platforms, by moving some employees to onshore (i.e., implementing remote operation capabilities) and replacing tasks in hazardous environments with automation and robotization. This leads to a transformation of future offshore drilling occupations. It is vital to understand these transformations and to predict future employment scenarios so that stakeholders can develop and implement education and training programs for reskilling existing workforce and orienting new employees.

B. Overview of the Proposed Job Merging Framework

An overview of the proposed job merging framework, which is illustrated in Fig. 1, consists of ten key components. The Career descriptions are assessed to determine key features and to rank skills required for specific job and to then determine career pathway costs and to rank order the pathways based on cost. In addition, technology adoption & employment literature is used to determine the susceptibility of these jobs to automation and to determine the trajectory for automation over time. The automation susceptibility trajectories and the career pathway ranking are used to identify the optimal job merging scenarios.

Career Description: It is necessary to identify the occupations associated with specific industrial settings and their associated job descriptions. For an offshore drilling platform, 40 occupations (refer to Table XIV in Appendix A for complete list) were identified for key roles during drilling operations. Since this study aims to evaluate the evolution of offshore drilling occupations with technological adoption, onshore support occupations, such as purchasing clerks and supply chain supervisors, were not included among the relevant careers. Representative job descriptions for the 40 occupations were created using various online resources. Section III-C presents this process along with the brief introduction to the online resources used for creating representative job descriptions. The key information for each job description includes the duties and responsibilities, the education and industrial training

requirements, and the required amount of prior work experience to be able to perform the job.

Feature Selection and Skill Ranking: Once the job descriptions are created, similarities between different jobs are analyzed to identify the least disruptive way to merge jobs. This study uses twelve features to compare the similarities between multiple jobs. For each job, based on the job descriptions, a relative ranking is assigned for these features. Section III-D introduces the 12 features used in the study, while Section III-E presents the initial ranking for these features.

Career Pathway Cost Calculation: Once the skill ranking for each job is assigned, the proposed framework calculates a cost matrix that represents how easy or challenging it is to merge a given job with the rest of the existing jobs. The higher the cost, the greater the challenges of merging. Section III-F discusses the career pathway cost calculation process.

Career Pathway Ranking: The calculated cost matrix is then converted into a ranking matrix, which iteratively considers each job in the list and arranges the remaining other $N - 1$ jobs in a way that the job with the lowest career pathway cost is ranked one and the job with the highest career pathway cost is ranked $N - 1$, where N is the total number of jobs considered. The key difference between the career pathway cost matrix and the ranking matrix is that the former is an unsorted list while the latter is a sorted list. Section III-G presents the career pathway ranking calculation process.

Technology Adoption & Employment Literature: Besides the similarity between two jobs, the portion of tasks of each job that can be automated using the demonstrated technologies plays a critical role when merging jobs. For instance, let job_α and job_β be two jobs, each with 100 tasks that are non-automatable and job_β is ranked one in the job_α 's career pathway ranking, i.e., tasks associated with these two jobs are highly related. However, merging these two jobs is impossible as the newly created job will then have 200 tasks to do. Therefore, this study conducted a literature survey to extract automation susceptibility values for the selected 40 occupations. The collected data are listed in Table XIV.

Automation Susceptibility Trajectories: The collected automation susceptibility data gives two pieces of information: (i) the proportion of tasks that can be automated using existing technologies, and (ii) the probability of a given job being fully automated in the next 10-20 years [11], [13], [25]. By utilizing this information, the study presented in this article calculates the automation susceptibility trajectories for the selected 40 jobs over a 100 year period. More details on the susceptibility trajectory calculation is presented in Section III-H.

Following the steps noted above, all of the pairwise combinations of existing jobs are generated and combined with the susceptibility trajectories and the career pathway rankings to determine optimal job merging, as well as the

tentative timeline for the job merging and job creation. Also, the features are ranked for the newly created jobs. This process will be discussed in Section III-I. When two jobs are merged, a new type of occupation is created and the original jobs¹ disappear from the workforce. Therefore, the offshore drilling occupations' job structure will be modified at each job merging event. Newly created occupations and unmerged occupations are re-evaluated to develop new career pathway costs, career pathway rankings, the level of susceptibility to automation and possible subsequent job merging. This iterative process allows newly created jobs at an early stage of the timeline (say 2025) to merge with another new job or unmerged (original) job at the later stage of the timeline (say 2050). The proposed algorithm continues this iterative job merging process until the career pathway cost of possible job merging reaches a predefined upper threshold.

C. Career Descriptions

To perform a career pathway analysis, a large data set is required which includes key characteristics, such as knowledge, skills, abilities, education, experience, training, tasks, interests, work values, work styles, tools and technologies, work activities, etc., for each occupation. For example, the US O*NET online database lists over 1000 occupations along with descriptions and ranking for 120 occupation-related features [38]. These data are generated using a range of industrial surveys with over 67,000 responses. The O*NET data set is widely used for employment modelling and simulation purposes. With regard to the Canadian job market, the National Occupation Classification (NOC) system has been developed using national survey data to classify approximately 35,000 job titles into the 500 unit groups [39]. These 500 unit groups are then classified into the 140 minor groups which are then collected into 40 major groups which fall under 10 broad occupation categories. Each unit group presents a lead statement, sample job titles, inclusions and exclusions, primary duties, employment requirements, and additional information regarding career progression and transfers. The limitation of the NOC system for employment modelling is that a given unit group consists of multiple job titles which may not share the requirements pertaining to the level of skill, knowledge, abilities, work values, work styles and work activities. For example, "cement truck driver - oil field services", "chemical services operator - oil field services", "derrickman/woman - oil and gas drilling" and "dynamic positioning operator - offshore drilling" are listed under the unit group NOC 8412 - Oil and gas well drilling and related workers and services operators.² However, most of the job duties and requirements of these four jobs do not coincide. Therefore, without solely depending on NOC, this study develops job descriptions for the 40 offshore drilling related

¹These two jobs refer to source jobs or original jobs.

²Note that NOC 8412 unit group consists of 43 job titles. The four example titles presented here are extracted only to illustrate that the skill, knowledge, abilities, work values, work styles and work activities requirements of jobs listed in a given unit group not necessarily be identical for all the jobs contained in the unit group.

occupations by aggregating the information extracted from the following sources:

- *Atlantic Canada offshore petroleum standard practice for the training and qualification of offshore personnel* [40]: This report contains high-level job descriptions for most of the jobs associated with the offshore drilling installation and production installation.
- *Offshore oil and gas people - overview of offshore drilling operation* [41]: This book contains an overview of the people involved in offshore drilling operations, their lifestyles, and their responsibilities. Additionally, it categorizes offshore drilling personnel into three groups based on the employer: oil and gas company, drilling contractor, and third-party contractors.
- *Newfoundland and Labrador oil and gas career information website* [42]: This website contains comprehensive information about Newfoundland and Labrador's oil and gas industry, career profiles, education programs, ongoing projects, upcoming projects, career progression tables, etc.
- *Job advertisements from the internet*: A series of job advertisements were collected from several online job listing databases and oil and gas companies' career opportunity web pages.

D. Features for Career Pathways

Typically, skills, abilities, and knowledge features have been used to model and simulate future employment scenarios based on the impacts of technology. For example, work presented in [11] argued that perception and manipulation, creative intelligence, and social intelligence are the key bottlenecks for computerization. These three bottlenecks were considered in terms of nine O*NET variables (finger dexterity, manual dexterity, cramped workspace, and awkward positions, originality, fine arts, social perceptiveness, negotiation, persuasion, and assisting and caring for others) to perform quantitative analysis for future employment scenarios. An identical feature set based on Japanese occupation data was used in [43] to predict the susceptibility of the Japanese workforce to technological change. Work presented in [18] used all 120 features in the O*NET database to predict the future skill demands. The study presented in [15] used five capability groups, namely sensor perception, cognitive capabilities, natural language processing, social and emotional capabilities, and physical capabilities, to determine the portion of activities that can be automated using existing technologies.

The study presented in this article also follows the feature-based cost calculation approach to numerically rank the similarity between offshore oil and gas drilling-related occupations. As this study investigates ways to merge existing jobs to execute tasks that are not automatable using the demonstrated technologies, we select a set of features that can define similarities between given two jobs along four dimensions: intellectual, cognitive, physical, and social capabilities. When an employee assumes duties and responsibilities of an occupation, the person must possess a thorough intellectual background, including formal education, technical training, and awareness of the rules and regulations

associated with the occupation. Technical training may be acquired through a formal professional training program or on-the-job training. Therefore, level of education, work experience, exposure to new technologies, and awareness of rules and regulations are selected as features that can be used to compare intellectual similarities between two jobs and identify intellectual reskilling required to merge two jobs. Some occupations require employees to perform physically demanding tasks in hazardous working conditions. These employees need physical strength to conduct these manual tasks and a well-planned occupational training program to teach them correct postures when lifting and handling heavy items, operating heavy equipment and protecting them in hazardous working environments. Therefore, the amount of physical work and hazard level are selected as features that can be used to compare similarities between two jobs along the physical dimension. Some offshore drilling occupations have more responsibilities, ensuring the drilling operations run smoothly, precisely, and safely while others follow the directions provided by these individuals. Since each drilling operation is a unique task, these supervising level employees must have a high level of cognitive capabilities to propose unique solutions to unique issues promptly. To compare the similarities between two jobs along the cognitive dimension, this study use 'originality' and 'decision making' as features for career pathway cost calculation. Each occupation involves some level of social interaction. However, the level and type of interaction vary with jobs. For example, managerial jobs interact with stakeholders more frequently than drill-floor workers. Similarly, supervisors manage and guide employees under them to safely conduct their tasks while subordinates follow the directives of supervisors. When combining two jobs, it is essential to identify training required along these social dimensions and implement this training timely manner so that social conflicts can be minimized, if not eliminated. This study uses three features, i.e., stakeholder interaction, managing others, and instructing to compare similarities between two occupations along the social dimension. Apart from the eleven features introduced above, working groups broadly defines intellectual, cognitive, physical, and social skills required to be employed in an occupation. People tend to stay in the same working group instead of switching between groups more frequently. For example, there is a high similarity between tasks performed by a driller and an assistant driller compared to a driller and a chef. Therefore, merging a driller and an assistant driller is more reasonable than merging a driller with a chef. To account effect coming from working group, this study uses discipline as a feature for cost calculation. Table I summarizes the twelve features which are used in this study.

E. Initial Feature Ranking for Individual Occupation

Except for the *work experience*, *discipline* and *education* features, all other features are ranked using a five-point scale: extremely (5 points), very (4 points), moderately (3 points), slightly (2 points), marginally (1 point). The work experience requirements listed in job advertisements, [40] (manual for

TABLE I
FEATURES FOR CAREER PATHWAY COST CALCULATIONS

Feature	Description
Discipline	Which working group that the job belongs to
Education	The level of education required for the job
Work experience	Number of years of experience required for the job
Technological expertise	The level of knowledge on the emerging technology and the ability to adopt new technologies
Knowledge of regulation and policies	The ability to comply with regulations and policies and guide other to do so.
Level of hazardous	The level of hazardous involves
Amount of physical work	The ability to perform physically intensive activities
Judgment and decision making	The ability for considering the relative costs and benefits of potential actions to choose the most appropriate one
Originality	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem
Stakeholder interaction	Being aware of others' reactions and understanding why they react as they do and finding common ground to operate
Managing others	The ability to negotiate, persuade, and coordinate others
Instructing	The ability to teach others how to perform some tasks

TABLE II
SKILL TYPES OF CANADIAN WORKFORCE

Skill type	NOC First digit
Management occupations	0
Business, finance and administration occupations	1
Natural and applied sciences and related occupations	2
Health occupations	3
Occupations in education, law and social, community and government services	4
Occupations in art, culture, recreation and sport	5
Sales and service occupations	6
Trades, transport and equipment operators and related occupations	7
Natural resources, agriculture and related production occupations	8
Occupations in manufacturing and utilities	9

Atlantic Canada offshore petroleum standard practice for the training and qualification of offshore personnel) and [42] (career information web site of petroleum industry human resource committee Newfoundland & Labrador) are combined to develop the ranking for the *work experience* feature.

The *discipline* feature represents the working group to which the job belongs. This study uses NOC codes to determine the working group for each job. As mentioned earlier, the NOC codes for the Canadian workforce categorizes approximately 35,000 jobs into 10 broad occupation categories (also known as skill types), 40 major groups, 140 minor groups and 500 unit groups. The 10 broad occupation categories are listed in Table II.

For a given broad occupation category, the percentage of transferable skills between two occupations is highest if the two occupations are from the same unit group and is lowest if the two occupations are from different major groups.

Although the percentage of transferable skills decreases when moving from unit group to minor group to major group, the reskilling cost to transfer from one broad occupation category to another is not necessarily higher than the reskilling cost to transfer between two jobs in the same unit group. For example, the reskilling cost is lower when transferring from “derrickman/woman - oil and gas drilling” (NOC 8412) to “server - food and beverage services” (NOC 6513) while there is some level of reskilling cost associated with transferring from “derrickman/woman - oil and gas drilling” to “chemical services operator - oil field services” (NOC 8412) although these two jobs are from the same unit group. Since the objective of our study is not to find the occupational transfer matrix but to find career pathways for job merging, the discipline changer costs are assigned to prioritize the job merging as follows: jobs from the same unit group are merged first; followed by the jobs from the same minor group, then jobs from the same major group and finally the jobs from different broader groups. To achieve this objective, the career changer cost for the *discipline* feature (CCD) is set to 100, 200, 400, and 900 if the two source jobs are in two-unit groups, minor groups, major groups and broad occupation categories, respectively.

Among the 40 occupations directly associated with the offshore oil and gas industry, only a few occupations would be preserved without merging with others. Consider a drilling platform that is not fully automated or is remotely operated with few personnel onboard (POB). In this case, a medic is required to be onboard to provide emergency and routine medical services. Similarly, it is necessary to have a person to prepare and serve food for the POB. Lastly, a top-ranked officer like an offshore installation manager (OIM) must be onboard to make critical decisions promptly and oversee the entire operation to ensure that the activities comply with the international, national and local regulatory standards. The skill-type index, i.e., the first digit of a given NOC code, of OIM, medic and food service-related occupations are 0, 3 and 6, respectively. The CCD for changing skill-type to and from these three categories are set to relatively very high values compared to the rest of the skill-type transfers. Table III summarizes the broad occupation category transfer costs used in this study. This study assigns a higher CCD for transferring to and from high-level supervisory positions. This modification merges multiple high-level supervisory positions to a single supervisory job. Except for the OIM, all of the high-level supervisory jobs associated with an offshore drilling installation have the same NOC code, i.e., 8222. Therefore, the cost of discipline change to and from NOC 8222 is set to 1500.

The point scale for the *education* feature is assigned using the Canadian NOC codes. The first digit of the NOC code represents the broad occupation category, also known as skill type (refer to Table II). Except for the management occupations (skill type 0 occupations), the second digit represents the skill levels (refer to Table IV) which are defined using the educational requirements of the jobs. The third and fourth digits of the NOC code represent the minor group and unit group levels, respectively. From Table IV, it can be seen that the higher the second digit the lower the required

TABLE III
CHANGER COST FOR 'DISCIPLINE' FEATURE FOR BROAD OCCUPATION CATEGORY CHANGING[†]

First digit of NOC code (Skill-type index)	0	1	2	3	4	5	6	7	8	9
0	0	1000	1000	1000	1000	1000	1000	1000	1000	1000
1	900	0	900	2000	900	900	2500	900	900	900
2	900	900	0	3000	900	900	2500	900	900	900
3	5000	5000	5000	0	5000	5000	5000	5000	5000	5000
4	900	900	900	2000	0	900	2500	900	900	900
5	900	900	900	2000	900	0	2500	900	900	900
6	2500	2500	2500	2500	2500	2500	0	2500	2500	2500
7	900	900	900	3000	900	900	2500	0	900	900
8	900	900	900	2500	900	900	2500	900	0	900
9	900	900	900	2500	900	900	2500	900	900	0

[†]: Table must be read as going from column index skill type to row index skill type.

TABLE IV
CANADIAN EMPLOYMENT SKILL LEVELS

Skill level	Second digit	Description
A	0, 1	Bachelor's, Master's or doctorate
B	2, 3	2-4 years post secondary education
C	4, 5	Secondary school
D	6, 7	No formal educational requirements/Short work demonstration or on-the-job training

TABLE V
POINT RANKING FOR EDUCATION

Second digit	0	1	2	3	4	5	6	7	8
Point rank	14	13	9	8	5	4	2	1	10

education level. Therefore, the lowest education point rank, i.e., one, is assigned to the highest second digit, i.e., seven. Within the same skill level (A, B, C, or D), education point rank is increased by one when the value of the second digit is decreased by one. Transfer between skill levels is ranked differently to incorporate the increase in challenge to transfer from non-formal education to secondary school education (2-point step change), secondary school education to post-secondary education (3-point step change), and post-secondary education to graduate studies (4-point step change).

Note that skill level categorization uses numbers in the range of zero to seven (Table IV). However, this categorization is not defined for management occupations (skill type-0). The only skill type-0 job involved in the offshore drilling operation is OIM, which belongs to NOC 0811. From the job advertisements, it was noted that the educational requirement of an OIM is between the upper limit of skill level-B and the lower limit of skill level-A, with more bias towards skill level-B. Therefore, this study assigned a higher education point rank for the OIM than for the jobs in skill level-B, and a lower education point rank for the OIM than for the jobs in skill level-A. Table V lists the final ranking for the education feature along with the associated second digit of NOC codes.

F. Career Pathway Cost Calculation

Feature ranking mismatches between jobs are applied to compute the career pathway costs. When merging an upper

skill job with a lower skill job, education and training programs are required to reskill the employees in those jobs. The reskilling cost for a high-skill employee to perform a low-skill job differs from the cost for a low-skill employee to perform a high-skill job. Therefore, when considering pairwise job merging, it is important to identify whether this is an upward or a downward skill transfer and to assign scaling (weighting) factors independently for each feature.

Career pathway cost (CPC) to merge jobs i and j , such that an employee in job i is reskilled to perform the non-automatable tasks of both the jobs, is computed as

$$CPC_{j,i} = \sum_{n=2}^{12} k_n (f_{j,n} - f_{i,n})^2 + k_1 CCD_{j,i} \quad (1)$$

where, k_n represents upward/downward weighting factor for n^{th} feature, $f_{i,n}$ represents feature ranking for n^{th} feature of i^{th} job, $f_{j,n}$ represents feature ranking for n^{th} feature of j^{th} job, $CPC_{j,i}$ represents the career pathway cost to reskill an employee in job i to performed the non-automatable tasks of both jobs, and $CCD_{j,i}$ represents the changer cost for the *discipline* feature. Note that the *discipline* feature corresponds to the first feature in the feature list. The cost of changing the discipline is calculated separately, as presented in Section III-E. This costs is directly added to the calculated cost due to the changes in other features, i.e., features two to twelve.

The scaling factor k_n defines, for feature n , the relative level of challenge to change upward or downward. This is also assigned using a five-point scale where five represents extremely challenging, and one represents minimal challenge (or no challenge at all). Scaling factors assigned for upward and downward movements for the twelve features of interest are listed in Table VI.

Upward skill transfer usually has a higher relative weight than a downward skill transfer because moving upward requires the employee to develop a new skill, while moving downward typically does not have such a requirement. When it comes to the *amount of physical work* and *level of hazardous*, in this study, going upward implies that moving to a job that involves fewer physical activities and is less hazardous. Therefore, moving upward is more favourable than moving downward, with a lower relative weight for upward movement compared to downward movement. For the *education* feature,

TABLE VI

RELATIVE WEIGHTS FOR UPWARD AND DOWNWARD SKILL TRANSFERS

Feature	Upward	Downward
Discipline	2	2
Education	3	4
Work experience	4	5
Technological expertise	4	1
Knowledge on regulation and policies	3	1
Level of hazardous	1	4
Amount of physical work	2	4
Judgment and decision making	5	1
Originality	5	1
Stakeholder interaction	4	2
Managing others	4	2
Instructing	4	2

moving upward implies that an employee with lower education credentials is required to attend school, college or university to obtain new (higher) education credentials. Moving downward in education implies that an employee with higher education credentials is required to work in a lower skill job. When considering the existing organizational structure, policies, education, and training opportunities, acquiring a new education credential is relatively easier than hiring someone with higher education credentials to perform lower skill jobs. For example, companies do not assign or hire a person with a doctoral degree to perform the tasks that high school graduates can do. Therefore, a downward transfer of education is penalized more than an upward transfer. The same principle is applied to the *work experience* feature, since acquiring more work experience is relatively easier than assigning a highly experienced person to perform tasks that an entry-level (no-experience) employee can do. As the *discipline* feature determines the change in a workgroup, the concept of upward/downward skill transfer does not apply to it. Therefore, this study assigns a constant (equal) relative weight for upward/downward transfer for the *discipline* feature.

Algorithm 1 outlines the procedure for career pathway cost calculation. It initializes with a known feature ranking as discussed in section III-E, upward/downward scaling factor matrices, NOC codes, and data to compute CCD. Then, for each job, the career pathway cost to all other jobs is calculated and the results are stored in the career pathway cost matrix (CPCM). The dimension of the CPCM is $N \times N$, where N is the number of occupations under study. The diagonal elements of this matrix become zero because there is no cost when there is no changing between jobs.

G. Career Pathway Ranking

Each element in a column of the CPCM represents career pathway cost from a given job each of the other jobs. To determine the career pathway ranking matrix (CPRM), the individual column of CPCM is sorted in ascending order independently and assigned the career pathway ranking in the range of 1 to $N - 1$ as shown in Algorithm 2. Therefore, merging with the smallest CPC corresponds to a rank of one, while merging with the largest CPC corresponds to a rank of $N - 1$. The lower the CPRM value, the greater the similarity between two jobs which means they are easier to merge.

Algorithm 1 Career Pathway Cost Calculation Algorithm

Data: initial feature ranking matrix, upward/downward scaling factors, NOCs, data to calculate CCD
Result: career pathway cost matrix (CPCM)

- 1 initialization: $CPCM = \text{zeros}(N \times N)$
- 2 **for each job in the list (say i) do**
- 3 **for each job in the list (say j) do**
- 4 Compute career pathway cost ($CPC_{j,i}$) using equation (1)
- 5 $CPCM(j, i) = CPC_{j,i}$

Algorithm 2 Career Pathway Ranking Calculation Algorithm

Data: career pathway cost matrix (CPCM)
Result: career pathway ranking matrix (CPRM)

- 1 initialization: $CPRM = \text{zeros}(N \times N)$
- 2 **for each column in CPCM do**
- 3 Sort the column in ascending order
- 4 Assign career pathway ranking in the range 1 to $N - 1$

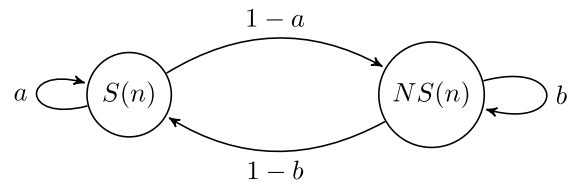


Fig. 2. Two-states Markov chain.

H. Jobs' Susceptibility for Automation

As outlined in Section II, there are numerous studies modeled the susceptibility of a given job to automation and computerization. This paper adapts the work presented in [14], [44], [25], [15], [11], [11], and [13] to compute the susceptibility of the offshore drilling occupations over a period of 100 years. This is the span of the simulation. It does not alter the study results since all the possible job merging occurs within 40 to 60 years, depending on the digital readiness level that has been used for evaluation.

1) *Compute General Susceptibility Trajectories:* A two state Markov chain shown in Fig. 2 is applied to compute the susceptibility of a given job to automation (digitalization). This Markov chain follows a linear system given in (2) where $S(n)$ represents the susceptible labour and $NS(n)$ represents the non-susceptible labour. The value of $S(n)$ and $NS(n)$ are in the range of zero to one and their summation should equal to one, i.e., $0 \leq S(n) \leq 1$, $0 \leq NS(n) \leq 1$ and $S(n) + NS(n) = 1$ for $n > 0$ where n is the simulation time step.

$$\begin{bmatrix} S(n) \\ NS(n) \end{bmatrix} = \begin{bmatrix} 1 & 1-b \\ 1-a & a \end{bmatrix} \begin{bmatrix} S(n-1) \\ NS(n-1) \end{bmatrix} \quad (2)$$

In this Markov chain, it is assumed that a portion of the susceptible labour, $aS(n)$, remains susceptible, while the rest,

$(1 - a)S(n)$, moves back to the non-susceptible labour due to regulatory changes. Similarly, a portion of non-susceptible labour, $bNS(n)$, remains non-susceptible, while the rest, $(1 - b)NS(n)$, moves to the susceptible labour due to technology adoption and/or regulatory requirements. The parameters a and b represent the probability that the tasks in a given job remain as susceptible labour and non-susceptible labour, respectively. Note that $(1 - b)$ represents the probability of changing from non-susceptible to susceptible labour; thus, the susceptibility values given in [11], [11], and [13] (Oxford percentages) can be used to represent this quantity. The susceptibility values given in [44], [25], [15], and [13] (McKinsey percentages) are used as the initial value for $S(n)$. The simulation time step, i.e., time step for the Markov chain, is set to ten years. A smooth spiral-based curve fitting approach is then used to interpolate missing susceptibility values between two simulation time steps.

2) *Compute Initial Oxford Trajectories*: The fourth industrial revolution is accelerating innovation and digitalization. Such acceleration could see the Oxford percentages reported in [11], [11], and [13] increase with time. Therefore, a logistic regression-based approach is applied to compute the trajectories for Oxford percentages. For the input data set, it is assumed that the start year for Oxford trajectories is 2018, corresponding to the year of the Oxford study, and the year of the anticipated Oxford value is 2038. Note that the Oxford values gives the probability of a given job being fully automated in the next 10-20 years [11], [13], [25]. The Oxford values at 2018 (the starting year) are assumed as 1%.

3) *Digital Readiness Levels*: It was proposed that there are five factors affecting the pace and extent of technology adoption [15]. These factors are:

- **Technical feasibility**: The existing industrial and demographic challenges may be solved by deploying demonstrated (existing) technologies. However, in some scenarios, technology has to be developed and integrated, requiring an extended time frame for technology adoption.
- **Cost of developing and deploying solution**: Development and deployment of technologies involve a series of costs, including hardware and software costs as well as taxes. These additional costs may affect the pace of technology adoption.
- **Labour market dynamics**: The supply, demand and costs of human labour can catalyze or hinder automation and digitalization.
- **Economic benefits**: While pure labour cost savings may not drive technology adoption, other economic advantages such as improved quality and throughput integrated with labour cost saving could be drivers. The existence or absence of such economic benefits either accelerates or decelerates technology adoption.
- **Regulatory and social acceptance**: Social influence may bring new regulations to either support or oppose the technology adoption.

The Oxford and McKinsey projections were based on technological readiness but did not account for the other four abovementioned factors. These four factors cause technology

TABLE VII
TEN-POINT SCALE FOR DR LEVEL

Digital readiness level	S	t_o
1 (Low)	100	2050
2	90	2046
3	80	2043
4 (Medium)	70	2040
5	60	2037
6	50	2034
7 (High)	40	2031
8	30	2028
9	20	2025
10 (Very high)	10	2021

adoption to lag technological feasibility, [15], requiring to modify the susceptibility trajectories calculated in the last two steps. Unfortunately, there is no sufficient quantitative data to model these four factors. Therefore, this study adopted the standard logistic growth curve (S-curve) approach that has been used for centuries to project future scenarios for many application domains, including ecology, medicine, chemistry, physics, linguistics, agriculture, economics, and sociology [45], [46], [47], [48], [49], [50], [51], [52] to project the growth curves for digital adoption. Equation (3), gives the standard logistic growth curve, where $f(t)$ represents the parameter of interest at time t , t_o represents t values of the sigmoid's midpoint, L represents the supremum of $f(t)$, and k represents the steepness of the curve.

$$f(t) = \frac{L}{1 + e^{-k(t-t_o)}} \quad (3)$$

For our study, $f(t)$ gives digital readiness (DR) projection, which varies from zero to one (i.e., 0% to 100%), in year t . Therefore, $L = 1$ (i.e., 100%) and t_o represent the year that the technology adoption is at 50% of its final value. Suppose sufficient data is available representing the aggregated effect of the five factors that affect the pace and extent of technology adoption. In that case, it will be possible to perform nonlinear least square estimation to calculate parameters k and t_o . Since such data is unavailable, we consider ten DR scenarios as summarized in VII, and calculate the steepness of the curve, i.e., k , as $-(\ln 10^{-6})/S$ where S gives the numbers of years needed to reach the supremum, i.e., L , of DR. Ten synthesized DR growth curves are shown in Fig. 3.

4) *Updated Susceptibility Trajectories*: For a given job, the susceptibility trajectories calculated in Section III-H1 are updated by multiplying them by the calculated DR growth curve. This updating step generates ten different susceptibility trajectories per job. For example, the updated susceptibility trajectories and Oxford-McKinsey-based original susceptibility trajectory for Offshore Installation Manager are shown in Fig. 4.

I. Job Merging

The proposed job merging approach is outlined in Algorithm 3. The inputs to the job merging algorithm include the existing job titles, the associated NOC codes, the McKinsey and Oxford percentages, the year to the anticipated Oxford value, the simulation start year and time

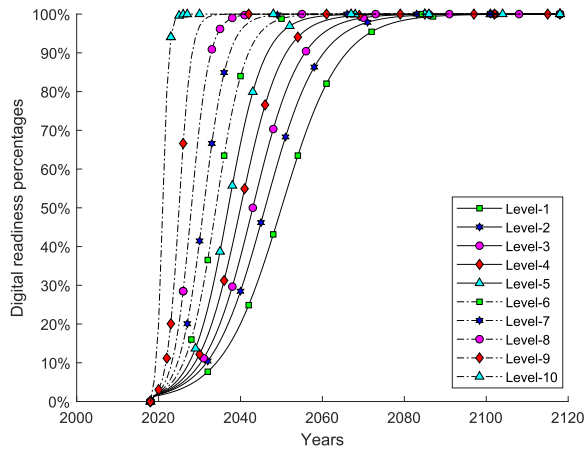


Fig. 3. Digital readiness levels. The readiness levels are in the one-to-ten scale where Level-1 represents the lowest digital readiness and Level-10 represents the highest digital readiness.

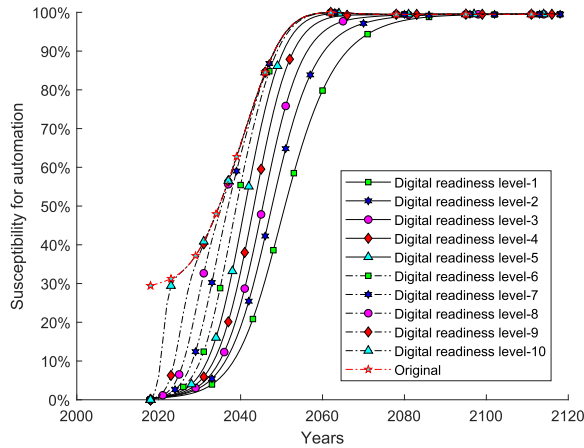


Fig. 4. Susceptibility of OIM for automation.

window, the feature value matrix for existing jobs, the upward and downward skill transfer weights, and the weights for transferring between different skill types (broad occupation categories). Values for the first four parameters are given in Table XIV (Appendix A). It is assumed that the year to the anticipated Oxford values for the existing jobs is 2038 (20 years from the starting year). The simulation start time is set to 2018, and the simulation time window is set to 100 years. Feature values used for existing jobs are listed Table XV (Appendix B). The upward and downward skill transfer weights are given in Table VI (Section III-F). As discussed in Section III-E, the discipline change cost is derived using the NOC codes. Thus, the NOC codes are listed as feature values for the *Discipline* vector. The weight for the skill type (broad occupation group) transfer is given in Table III (Section III-E).

The algorithm initializes with calculating the digital readiness levels. The Oxford trajectories, the general susceptibility trajectories, and the updated susceptibility trajectories are then calculated for each digital readiness level. The job merging iterations follow this. The proposed algorithm first computes the career pathway cost matrix for the input jobs at the first iteration. This step is followed by the calculation of the career

Algorithm 3 Job Merging Algorithm

Data: Job titles, NOCs, McKinsey percentages, Oxford percentages, year to know Oxford %, start year, simulation time window, feature values for existing jobs, weight for moving up, weights for moving down, weights for skill type transfers

Result: Future occupation scenarios

- 1 Initialization: Compute digital readiness levels (Section III-H3)
- 2 Compute Oxford trajectories for each job (Section III-H2)
- 3 Compute general susceptibilities for each job (Section III-H1)
- 4 Compute the updated susceptibilities for each job (Section III-H4)
- 5 **for** each digital readiness level **do**
- 6 **while** jobs can be merged **do**
- 7 Compute CPCM (Algorithm 1)
- 8 Compute CPRM (Algorithm 2)
- 9 **for** each column of CPRM **do**
- 10 **for** each entry of the column **do**
- 11 **if** CPC < threshold **then**
- 12 Create new job
- 13 **if** No job has created **then**
- 14 Break the while-loop
- 15 **for** each new job **do**
- 16 Add susceptibility values of source jobs
- 17 Find year of job merging (Y_m^i)
- 18 Determine the smallest value for job merging year (say $\min(Y_m^i)$)
- 19 Select the job merging in the time window of $\min(Y_m^i)$ to $(\min(Y_m^i) + 5)$
- 20 Discard the rest of the job merging scenarios
- 21 Sort the selected job merging scenarios in ascending order of CPC
- 22 Analyse this list to determine and remove the multiple use of source jobs
- 23 **for** each job merging **do**
- 24 Merge two jobs
- 25 Compute new susceptibility values
- 26 Compute values for features
- 27 Remove the source jobs from job list
- 28 Add new job to the occupation list

pathway ranking matrix. Dimensions of these matrices are $N \times N$ where N is the number of jobs in the input data set of the current iteration. A sample career pathway cost matrix and ranking matrix are given in Table XVI and Table XVII, respectively (Appendix B).

For each entry in the CPRM, except for the diagonal elements, a new job is created by merging the column index job with the row index job. This results in a maximum of $N \times (N - 1)$ pairwise job merging scenarios for the list of N

jobs. If the career pathway cost is higher than a pre-defined threshold for a given job merging scenario, this particular job merging scenario is discarded. In our study, 2000 is used as the upper threshold. This upper bound is set to ensure Medic, OIM and Food services-related occupations are not merged with others and remain intact as long as someone is onboard an offshore drilling installation.

For the remaining job merging scenarios, the susceptibility values of source jobs are added to create a combined susceptibility of the source jobs. These combined susceptibility values range from 0% to 200%, where 0% indicates that both of the source jobs are not susceptible to automation, while 200% indicates that both of the source jobs are entirely (100%) susceptible to automation. For a given job merging iteration (say i^{th} job merging iteration), the year that the combined susceptibility first exceeds 120% is considered to be the year of job merging, Y_m^i for those jobs. Note that 100% would be the ideal threshold level for combined susceptibility to determine Y_m^i because 100% ensures that the newly created job has no activities left that can be automated using the demonstrated technologies at Y_m^i . However, this is an overly optimistic assumption, and this study considers 120% as the threshold level for the combined susceptibility to determine Y_m^i , to provide a margin for potential deviations that may occur during practical industrial implementations of automation.

For all of the possible job merging scenarios, the corresponding Y_m^i are calculated. If two source jobs are highly susceptible to automation, the summation of these susceptibility values will exceed 120% very quickly. In contrast, if two source jobs are not susceptible to automation, the summation of the two susceptibility values will take more time to exceed the 120% threshold. Therefore, Y_m^i values of the possible job merging scenarios are reviewed to determine the lowest Y_m^i value denoted as $\min(Y_m^i)$ (line 18, Algorithm 3).

In a list of many jobs, we may end up with several hundreds of options where a given job becomes a member of multiple job merging scenarios. For example, job_1 can be a member of multiple job merging scenarios such as $(job_1 + job_5)$, $(job_1 + job_{15})$, $(job_{10} + job_1)$, $(job_{17} + job_1)$, $(job_{21} + job_1)$, etc.. This study assumes that if a given job is merged with another job, both jobs become unavailable for subsequent job merging steps. This constraint is introduced to ensure that the job merging process leads to a decrease in POB rather increase in POB. Therefore, when a given job is a member of multiple job merging scenarios, the lowest-cost option is selected, and the higher-cost options are discarded. Suppose it is desirable to perform job merging as early as possible and to allow CPC to play a critical role in the job merging approach. In such a case, it is better to analyze the job merging scenarios that occur at $\min(Y_m^i)$ and the job merging scenarios that occur within a pre-defined time window from the $\min(Y_m^i)$ to find the optimum sequence of job merging. This study selects the job merging scenarios that exceed the combined susceptibility of 120% during the period of $\min(Y_m^i)$ to $(\min(Y_m^i) + 5)$ for further analysis (line 19, Algorithm 3). Any job merging scenario that occurs after $(\min(Y_m^i) + 5)$ is discarded for the current job merging iteration (line 20, Algorithm 3). The rationale for selecting a five-year time window from $\min(Y_m^i)$ as a threshold

is because the half-life of a learned skill³ being proposed to be five years [53], [54]. This pruning process allows jobs created at an early iteration to combine with an existing job or another newly created job at later iterations.

To limit one job to be merged with one another job and perform job merging as early as possible while giving a high priority to the job merging scenarios with lower CPC, the job merging scenarios for $\min(Y_m^i)$ to $(\min(Y_m^i) + 5)$ time window are first arranged in the ascending order of CPC (line 21, Algorithm 3). Then, starting from the lowest cost option, the elements of the sorted job merging list are evaluated to identify the multiple uses of the same job and to remove higher cost options (line 21, Algorithm 3). This is achieved by creating a list, say list-A, that contains source jobs that have already been considered for the current job merging iteration. The list is initialized by inserting two source jobs of the job merging scenario with the lowest CPC. Then the source jobs of the job merging scenario with the second lowest CPC are compared with the jobs in list-A. If at least one of the source jobs of the job merging scenario with the second lowest CPC is a member of list-A, this job merging scenario is discarded. Otherwise, it is considered a valid job merging scenario, and the list-A is updated by appending the source jobs of this job merging scenario. This process continues until all the selected job merging scenarios, going from the third lowest CPC to the highest CPC - one at a time, have been considered.

As a final step, new jobs are created using the job merging scenarios that remain after the pruning step at line 22 of Algorithm 3. Once two jobs are merged into one, the source jobs are removed from the occupation list, and a newly created job is added to the occupation list of offshore drilling installation. The proposed algorithm computes the susceptibility percentages and the ranking of features for the newly created jobs to ensure a continuum of job merging iterations.

The susceptibility value for a newly created job is calculated by subtracting 100% from the combined susceptibility value of the two source jobs at the merging. Except for the *level of hazardous*, *amount of physical work*, and the *discipline* features, the ranking of the other features of a newly created job is set to the maximum value of the corresponding feature ranking of the source jobs. The *level of hazardous* and the *amount of physical work* features of the new job are set to the average of the corresponding feature ranking of the source jobs. The *discipline* feature of the new job is set to the NOC code of the highest skilled job of the two source jobs. The second bit of the newly created NOC code is reset to the highest education level required for the source jobs. This process is iterated until no more job merging is possible.

IV. RESULTS

A. Simulation Environment

The proposed algorithm projects possible job-merging scenarios for the next few decades, which is not a rapidly

³This means that much of what someone learned ten years ago is obsolete and half of what they learned five years ago is no longer relevant for the present world.

TABLE VIII
VALIDATION CASE STUDY WITH TEN DRILLING RIG OCCUPATIONS

Job title	Calculated career pathway cost	Calculated career pathway rank
Roustabout	0	0
Roughneck	77	1
Motorman	944	2
Assistant Derrickman	949	3
Derrickman	1075	4
Assistant driller	1175	5
Driller	1225	6
Toolpusher	3535	7
Rig superintendent	3663	8
OIM	3977	9

changing parameter that requires real-time observation and instantaneous action to avoid catastrophic failures. Therefore, the minimized computational complexity and the algorithm's real-time execution capability are not the focus of this study. We implemented and simulated the proposed algorithms in MATLAB because it is a user-friendly programming and numeric computing platform with many inbuilt mathematical libraries. The software was installed in a laptop computer with a dual-core Intel Core i7-4510U CPU with multi-threading, operating at 2.00 GHz and 16 GB of RAM. On average, the processing time of the algorithm was less than two minutes, which included the read and write time of data and results for each job merging iterations.

B. Validation of Career Pathway Generation Process

To validate the proposed model, ten occupations related to offshore drilling operations were isolated and evaluated through Algorithm 1 and Algorithm 2. These ten occupations are roustabout, roughneck, motorman, assistant derrickman, derrickman, assistant driller, driller, tool pusher, rig superintendent, and OIM. The rationale for selecting these ten occupations is that their career progression path is well known. For example, someone can start as a roustabout and then progress to OIM following the path roughneck, motorman, assistant derrickman, derrickman, assistant driller, driller, toolpusher, rig superintendent, and finally, OIM [42]. The career path cost and the ranking for a roustabout to reskill to perform the task of the other nine jobs, as calculated by the proposed algorithms, are given in Table VIII. The result illustrates that, for a roustabout, the reskilling cost to become other nine occupations increases in the ascending order of career progression. This is consistent with [42] and demonstrated that the proposed framework can capture realistic career pathways. Note that a change to supervisory positions, such as toolpusher, rig superintendent and OIM, has a relatively high career pathway cost since the transfer costs for the *discipline* feature have relatively high values for merging with the OIM job (refer to Section III-E for more details.).

C. A Sample Job Merging Simulation

The proposed job merging approach develops a timeline for the evolution of jobs, i.e. new jobs to emerge and existing jobs to disappear. This study considers eleven simulation

cases where the first job merging simulation is performed purely on the technological feasibility, without integrating the digital readiness levels. The remaining ten simulation cases correspond to individual digital readiness levels. The timeline for the evolution of jobs for digital readiness level five (DRL5) is shown in Table XVIII (Appendix C). The first column of the table represents the job title, the second column represents the starting year, Y_s , of the job and the last column gives the life span, Y_{LS} , of the job. This result is presented to illustrate some important characteristics of the proposed job merging algorithm.

The job merging process was started with 40 occupations. If n pairwise job merging events occurs at a given iteration, the total number of occupations will be reduced by n . For the case of DRL5, the total number of iterations was six, reducing the POB to six. These six occupations include OIM, medic, a food service related job, a supervisory job, a general labour (low-skilled and medium-skilled) position and a high-skilled labour position. In Table XVIII, these six jobs are shaded in green.

The job title format of a newly created job encodes the reskilling direction information. For example, job title ($job_1 + job_2$) indicates that an employee in job_1 is reskilled to perform the task of both jobs while the job title ($job_2 + job_1$) indicates that an employee in job_2 is reskilled to perform the task of both jobs. While the proposed algorithm performs pairwise job merging, it may be economical and technologically feasible to combine more than two jobs at once. The iterative nature of the proposed algorithm effectively captures such situations. For example, in 2049, a new job ($job_\alpha + job_\beta$) is created combining job_α ((Dynamic Positioning Operator + Ballast Control Operator) + (Assistant Derrickman + Motorman)) with job_β ((Derrickman + Cement Pump Operator) + (Roughneck + Roustabout)). In Table XVIII, this job merging scenario is shaded in blue. This newly created job is then merged with job_γ (Radio Operator + Storekeeper) in the same year, i.e., 2049. As a result, the life span of ($job_\alpha + job_\beta$) became zero years, indicating that all three jobs are combined in a single step ($job_\alpha + job_\beta + job_\gamma$).

Note that the life span of some of the new jobs is very short. Investing in implementing new education and training programs to reskill or orient the workforce (existing and prospective) to perform jobs that have a shorter life span and asking the workforce to spend resources (monetary as well as time) to gain these skills do not lead to sustainable socioeconomic development, but may cause for a severe socioeconomic distress. For example, in 2041, a new job emerged by merging 'Chief Steward' and 'Steward,' shaded red row in Table XVIII. This new job is later merged with 'Cook' in 2043, resulting in another new job '(Chief Stewards + Steward) + Cook'. This implies that the life span of '(Chief Steward + Steward) is two years. Although reskilling of 'Chief Steward' to perform the tasks related to both jobs does not require new education or training programs, it will create socioeconomic distress as someone could view this as demoting 'Chief Steward' to 'Steward'. It may not be worth introducing such distress since the job lasts only two

TABLE IX
USE CASES FOR THE SENSITIVITY ANALYSIS

Sensitivity Analysis (SA)	Upward, downward weighting factor (K_n)	Feature values
SA-I	Changed	Unchanged
SA-II	Unchanged	Changed
SA-III	Changed	Changed

years. Alternatively, it might be appropriate to accelerate the technology adoption and combine these three jobs in 2041 or to delay technology adoption and combine these three jobs in 2043 in a single step. These observations imply that the stakeholders, including regulators, policymakers, education institutes, employers, trade unions, and subject matter experts, can use the results of the proposed algorithm only as a baseline to plan their education and reskilling programs, digitalization strategies, and human capital investments. Since the proposed algorithm provides all possible job merging scenarios, the stakeholders can implement, skip, accelerate or delay job merging steps to achieve optimum benefit from technology adoption and human capital investments while minimizing socioeconomic distress.

D. Sensitivity Analysis

The proposed algorithm follows a feature-based approach to calculate career pathway costs. The values for these features were determined by analyzing a range of literature and information gathered by attending two industrial conferences, two workshops, and multiple focus group discussions, which were focused on the digitalization of the offshore O&G industry. The fluctuation of these parameters could affect the overall cost calculation and, thus, the job merging pathways. Since this is the first study proposing the concept of job merging, no data is available in the literature to compare and validate the outputs of the proposed algorithm. Therefore, a sensitivity analysis (SA) was conducted to assess the robustness of the proposed algorithm against the parameter fluctuations.

As given in (1), calculated CPC depends on feature values and upward/downward weighting factor k_n . The following sensitivity analysis assesses how the job merging pathways will be affected if k_n changes (SA-I), if feature values change (SA-II), and if both k_n and feature values change simultaneously (SA-III) - as summarized in Table IX. In each case, the parameters under sensitivity analysis were changed up to 20% of their original value, both in upward and downward directions, in 5% steps. This implies that each SA scenario consists of eight assessments, totaling 24 assessments. Each assessment's resulting job merging pathways were compared with those given in Table XVIII.

If k_n or/and feature values are scaled, according to (1), the calculated CPC will also be varied. Therefore, the upper threshold of the CPC that prevents two jobs with high dissimilarities from being merged into a single job must also be updated with the change of parameter values. This upper threshold is predominantly defined by the value of *discipline*

TABLE X
SAMPLE CALCULATION OF SCALING FACTOR FOR THE UPPER THRESHOLD USING (4). THIS EXAMPLE CONSIDERS A 10% CHANGE IN THE UPWARD DIRECTION

Sensitivity Analysis (SA)	Variable	Sample calculation for +10% change
SA-I	k_n	$1.1 \times 1 = 1.1$
SA-II	Feature values	$1 \times 1.1 = 1.1$
SA-III	Both k_n and feature values	$1.1 \times 1.1 = 1.21$

TABLE XI
GROUPING OF JOB SENSITIVITY ANALYSIS SCENARIOS WITH IDENTICAL JOB MERGING PATHWAYS

	-20	-15	-10	-5	+5	+10	+15	+20
SA-I	*	*	*	*	*	*	*	*
SA-II	*	*	*	*	*	◆	◆	◆
SA-III	○	*	*	*	*	◆	◆	◆

feature compared to the other features. Therefore, the scaling factor for the upper threshold was approximated as the product of the scaling factor for k_n and CCD, which is given in (4) where SF_T , SF_{k_n} , and SF_{FV} represent scaling factors for the upper threshold, k_n , and feature values respectively. A sample calculation of the upper threshold scaling is given in Table X.

$$SF_T = SF_{k_n} \times SF_{FV} \quad (4)$$

Despite the variations in parameter values, each of the 24 assessment scenarios terminated the job merging process after six iterations, which is identical to the baseline case presented in the manuscript. Additionally, similar to the baseline results, each of the 24 assessment scenarios reduces POB from 40 occupations to six occupations. The number of job merging iterations and the final POB are independent parameters, although both become six in our simulations. The 24 assessment scenarios generated three distinct job merging pathways as grouped in Table XI. Three symbols, '*', '◆', and '○', represent similar job merging pathways. Out of 24 cases, 17 assessment scenarios (marked with '*' in Table XI) generated identical results compared to the baseline scenario given in Table XVIII, while the remaining seven cases followed two different pathways.

Table XII gives a more expanded view of the results presented in Table XI, wherein for each simulation case, it shows the final six jobs (say J1, J2, J3, J4, J5, J6) and whether these jobs follow identical job merging pathways compared to the baseline scenario, i.e., green highlighted jobs in Table XVIII. The jobs that followed identical job merging scenarios compared to the baseline scenario are shaded in green. Red or blue shading represents the jobs that follow different job merging pathways compared to the baseline scenario. As we can see, J1, J2, J3, J4, and J6 followed identical pathways for all 24 assessment scenarios. The preceding job merging steps in iterations one to five that led to J1, J2, J3, J4, and J6 at the sixth iteration were also identical to the corresponding merging in the baseline scenario. For 17 out of 24 assessment scenarios, J5 also followed the

TABLE XII

COMPARISON OF THE JOB MERGING PATHWAYS FOR 24 SENSITIVITY ANALYSIS ASSESSMENTS SCENARIOS. JOBS WITH IDENTICAL JOB MERGING PATHWAYS ARE HIGHLIGHTED IN SIMILAR COLOUR

		Percentage Change							
		-20%	-15%	-10%	-5%	5%	10%	15%	20%
SA-I	J1	J1	J1	J1	J1	J1	J1	J1	J1
	J2	J2	J2	J2	J2	J2	J2	J2	J2
	J3	J3	J3	J3	J3	J3	J3	J3	J3
	J4	J4	J4	J4	J4	J4	J4	J4	J4
	J5	J5	J5	J5	J5	J5	J5	J5	J5
	J6	J6	J6	J6	J6	J6	J6	J6	J6
SA-II	J1	J1	J1	J1	J1	J1	J1	J1	J1
	J2	J2	J2	J2	J2	J2	J2	J2	J2
	J3	J3	J3	J3	J3	J3	J3	J3	J3
	J4	J4	J4	J4	J4	J4	J4	J4	J4
	J5	J5	J5	J5	J5	J5	J5	J5	J5
	J6	J6	J6	J6	J6	J6	J6	J6	J6
SA-III	J1	J1	J1	J1	J1	J1	J1	J1	J1
	J2	J2	J2	J2	J2	J2	J2	J2	J2
	J3	J3	J3	J3	J3	J3	J3	J3	J3
	J4	J4	J4	J4	J4	J4	J4	J4	J4
	J5	J5	J5	J5	J5	J5	J5	J5	J5
	J6	J6	J6	J6	J6	J6	J6	J6	J6

TABLE XIII

THREE POSSIBLE JOB MERGING PATHWAYS FOR J5

J5	(((Driller+Assistant Driller)+(Electric Line Logging Engineer+Mudlogger))+((Maintenance Supervisor+Assistant Maintenance Supervisor)+(Crane Operator+Assistant Crane Operator)))+((Barge Supervisor+Assistant Barge Supervisor)+(Rig Electrician+Electronic Technician))+((Environmental Observer+Well tester)+Subsea Engineer))+((Drilling Engineer+(Completion Engineer+(Rig Mechanic+Rig Welder))))
J5	(((Barge Supervisor+Assistant Barge Supervisor)+(Rig Electrician+Electronic Technician))+((Environmental Observer+Well tester)+Subsea Engineer))+((Completion Engineer+(Rig Mechanic+Rig Welder)))+(((Driller+Assistant Driller)+(Electric Line Logging Engineer+Mudlogger))+((Maintenance Supervisor+Assistant Maintenance Supervisor)+(Crane Operator+Assistant Crane Operator)))+((Drilling Engineer))
J5	((Drilling Engineer+(Completion Engineer+(Rig Mechanic+Rig Welder)))+(((Driller+Assistant Driller)+(Electric Line Logging Engineer+Mudlogger))+((Maintenance Supervisor+Assistant Maintenance Supervisor)+(Crane Operator+Assistant Crane Operator)))+((Barge Supervisor+Assistant Barge Supervisor)+(Rig Electrician+Electronic Technician))+((Environmental Observer+Well tester)+Subsea Engineer))

same job merging pathway compared to the baseline case. For the cases highlighted in red and blue, the job merging pathway of J5 followed an identical pathway compared to the baseline scenario until the third and fourth iterations, respectively, and then deviated. However, as shown in Table XIII, the source jobs that composed J5 for red and blue cases also remained unchanged, although the sequence that they were merged is different compared to the baseline case (green). All these observations confirm that the proposed algorithm is robust against variations in the feature values and upward/downward weighting factor k_n .

TABLE XIV

EXISTING OCCUPATIONS IN OFFSHORE DRILLING OPERATION

Job title	NOC	McKinsey %	Oxford %
Offshore Installation Manager (OIM)	0811	29.5%	36%
Storekeeper	1522	85%	64%
Radio Operator	1525	40%	96%
Drilling Engineer	2145	19%	16%
Subsea Engineer	2145	19%	16%
Completion Engineer	2145	19%	16%
Rig Electrician	2241	23%	84%
Electronic Technician	2241	23%	84%
Environmental Observer	2255	39.5%	41.5%
Barge Supervisor	2273	76%	27%
Assistant Barge Supervisor	2273	76%	27%
Medic	3234	35%	4.9%
Cook	6322	81%	83%
Chief Stewards	6522	75%	35%
Steward	6522	75%	35%
Rig Welder	7232	87%	84%
Maintenance Supervisor	7301	63%	67.6%
Assistant Maintenance Supervisor	7301	63%	67.6%
Rig Mechanic	7311	60%	63%
Crane Operator	7371	85%	90%
Assistant Crane Operator	7371	85%	90%
Drilling Supervisor	8222	38%	17%
Rig Superintendent	8222	38%	17%
Toolpusher	8222	38%	17%
Mud Logging Supervisor (Operator)	8222	38%	17%
Completion and Intervention Supervisor (Operator)	8222	38%	17%
Well Test Supervisor	8222	38%	17%
Driller	8232	68.2%	77.2%
Assistant Driller (AD)	8232	68.2%	77.2%
Mudlogger	8232	68.2%	77.2%
Well tester	8232	68.2%	77.2%
Electric Line Logging (Wireline) Engineer	8232	68.2%	77.2%
Dynamic Positioning Operator (DPO)	8412	68.2%	77.2%
Derrickman	8412	68.2%	77.2%
Assistant Derrickman	8412	68.2%	77.2%
Ballast Control Operator	8412	68.2%	77.2%
Motorman	8412	68.2%	77.2%
Cement Pump Operator	8412	68.2%	77.2%
Roughneck	8615	27%	37%
Roustabout	8615	27%	37%

V. DISCUSSION

The available literature that predicts the susceptibility of existing jobs for automation mainly focuses on predicting the level of automation in the future workforce and potential emerging and declining jobs. However, these studies lack consideration of possible job merging scenarios due to task automation. Additionally, the existing literature is mainly concerned with technological readiness, with little to no focus given to the other modulating factors such as regulatory frameworks or social acceptance. Therefore, the results of those studies may be valid for specific industries under certain geopolitical conditions but do not generalize across industries and geographical regions. Addressing these two barriers, this article presented a method to utilize the existing literature to identify potential job merging scenarios along with a timeline under various digital readiness levels.

TABLE XV
FEATURE VALUES FOR INITIAL OCCUPATION LIST

	Discipline	Education	Work experience	Technological expertise	Knowledge on regulation and policies	Level of hazardous	Amount of physical work	Judgment and decision making	Originality	Stakeholder interaction	Managing others	Instructing
Offshore Installation Manager (OIM)	0811	10	8	5	5	1	1	5	5	5	5	4
Storekeeper	1522	4	3	1	3	3	3	1	1	4	2	1
Radio Operator	1525	4	2	3	3	1	1	5	2	2	1	1
Drilling Engineer	2145	13	8	5	4	2	1	5	5	4	4	4
Subsea Engineer	2145	13	4	4	3	4	3	4	4	2	3	4
Completion Engineer	2145	13	5	5	4	2	2	4	1	3	3	3
Rig Electrician	2241	9	4	4	2	4	2	3	3	1	3	3
Electronic Technician	2241	9	1	4	2	4	3	3	2	1	2	2
Environmental Observer	2255	9	0	3	4	1	1	5	2	1	1	1
Barge Supervisor	2273	9	2	4	5	1	1	4	4	4	4	4
Assistant Barge Supervisor	2273	9	1.5	4	4	1	2	3	3	3	4	4
Medic	3234	9	2	3	2	1	2	5	5	1	5	4
Cook	6322	8	1	1	1	2	3	1	1	1	1	1
Chief Stewards	6522	4	1	2	3	1	1	1	1	2	3	3
Steward	6522	4	0	1	1	1	3	1	1	1	1	1
Rig Welder	7232	9	5	3	2	4	4	3	2	1	1	1
Maintenance Supervisor	7301	8	6	4	4	1	1	4	4	3	4	4
Assistant Maintenance Supervisor	7301	8	4	4	4	2	2	3	3	2	3	3
Rig Mechanic	7311	8	3	4	2	4	3	3	3	1	3	3
Crane Operator	7371	8	2	3	2	2	3	4	3	1	4	4
Assistant Crane Operator	7371	8	0.5	3	2	3	3	3	2	1	3	3
Drilling Supervisor	8222	9	8	4	5	1	1	5	5	5	4	4
Rig Superintendent	8222	9	6	4	4	1	1	4	4	3	5	4
Toolpusher	8222	9	5	4	4	2	2	4	4	3	4	4
Mud Logging Supervisor (Operator)	8222	9	2	4	4	1	1	4	4	4	4	4
Completion and Intervention Supervisor (Operator)	8222	9	5	4	4	2	1	4	1	3	4	4
Well Test Supervisor	8222	9	3	3	1	2	2	3	1	2	3	3
Driller	8232	9	2	5	3	2	2	5	4	2	2	3
Assistant Driller (AD)	8232	9	1	4	2	2	3	4	4	3	3	4
Mudlogger	8232	9	2	3	1	3	2	3	1	1	1	1
Well tester	8232	9	0	3	1	2	3	2	1	1	1	2
Electric Line Logging (Wireline) Engineer	8232	9	3	3	1	2	2	3	1	2	2	2
Dynamic Positioning Operator (DPO)	8412	5	2	5	3	1	1	4	4	1	2	3
Derrickman	8412	5	4	3	2	3	3	4	4	3	3	4
Assistant Derrickman	8412	5	2	3	3	3	3	3	2	2	3	3
Ballast Control Operator	8412	5	2	4	3	1	1	4	4	2	2	3
Motorman	8412	5	2	3	3	3	3	3	1	2	3	3
Cement Pump Operator	8412	5	1	3	1	2	3	2	1	1	1	1
Roughneck	8615	2	1	3	1	5	4	2	2	3	3	3
Roustabout	8615	2	0	1	1	5	5	2	1	1	1	1

The proposed job merging algorithm is presented as a case study on the evolution of Canadian offshore oil and gas drilling occupations. However, this algorithm can be applied to other industries or occupation structures. The proposed algorithm projects that the total number of POB will be reduced to six from 40 within 30 years. These six occupations include an OIM, a medic, a food service-related job, a supervisory job, a general labour (low-skilled and medium-skilled), and a high-skilled labour position. The sensitivity analysis confirmed that the proposed algorithm is robust against variations in the feature values and upward/downward weighting factor k_n .

By using the results of the proposed algorithm, stakeholders, including regulators, policymakers, education institutes, employers (oil and gas operators and service companies), trade

unions, and subject matter experts, can obtain various insights. First, the algorithm provides possible job merging scenarios, allowing stakeholders to identify jobs that have high potential to be merged in the future and plan education and training programs timely manner to prepare the workforce

for these jobs. Second, the algorithm provides a tentative timeline for these job merging scenarios, allowing stakeholders to decide whether to implement, skip, accelerate or delay job merging steps to achieve optimum benefit from technology adoption and human capital investments while minimizing socio-economic impact. Third, as the algorithm provides tentative job merging scenarios and a timeline, the stakeholders can envision the required upgrade to their existing drilling platforms and how to design their future platform to blend seamlessly with the future workforce. By combining

TABLE XVIII

TIMELINE FOR EMERGING AND DISAPPEARING OF JOBS WHEN THE DIGITAL READINESS LEVEL IS FIVE. *Cont.* CONTINUE TO EXIST AFTER 100 YEARS FROM 2018, Y_s : STARTING YEAR, Y_{LS} : LIFE SPAN OF THE JOB

Job title	Y_s	Y_{LS}
[J1] Offshore Installation Manager	<2018	Cont.
Drilling Supervisor	<2018	29
Drilling Engineer	<2018	34
Dynamic Positioning Operator	<2018	22
Rig Superintendent	<2018	29
Toolpusher	<2018	29
Driller	<2018	22
Assistant Driller	<2018	22
Derrickman	<2018	22
Assistant Derrickman	<2018	22
Roughneck	<2018	25
Subsea Engineer	<2018	29
Barge Supervisor	<2018	23
Assistant Barge Supervisor	<2018	23
Ballast Control Operator	<2018	22
Mud Logging Supervisor	<2018	29
Maintenance Supervisor	<2018	22
Assistant Maintenance Supervisor	<2018	22
Rig Mechanic	<2018	22
Rig Electrician	<2018	22
Electronic Technician	<2018	22
Rig Welder	<2018	22
Crane Operator	<2018	21
Assistant Crane Operator	<2018	21
Roustabout	<2018	25
Storekeeper	<2018	22
Radio Operator	<2018	22
Environmental Observer	<2018	23
Completion and Intervention Supervisor	<2018	29
Completion Engineer	<2018	28
Motorman	<2018	22
Mudlogger	<2018	22
Well tester	<2018	23
Cement Pump Operator	<2018	22
Well Test Supervisor	<2018	29
Electric Line Logging Engineer	<2018	22
Chief Stewards	<2018	23
Steward	<2018	23
Cook	<2018	25
[J2] Medic	<2018	Cont.
(Crane Operator + Assistant Crane Operator)	2039	5
(Assistant Derrickman + Motorman)	2040	4
(Dynamic Positioning Operator + Ballast Control Operator)	2040	4
(Electric Line Logging Engineer + Mudlogger)	2040	4
(Driller + Assistant Driller)	2040	4
(Maintenance Supervisor + Assistant Maintenance Supervisor)	2040	4
(Rig Electrician + Electronic Technician)	2040	5
(Derrickman + Cement Pump Operator)	2040	6
(Radio Operator + Storekeeper)	2040	9
(Rig Mechanic + Rig Welder)	2040	6

TABLE XVIII

(Continued.) TIMELINE FOR EMERGING AND DISAPPEARING OF JOBS WHEN THE DIGITAL READINESS LEVEL IS FIVE. *Cont.* CONTINUE TO EXIST
AFTER 100 YEARS FROM 2018, Y_s : STARTING YEAR, Y_{LS} : LIFE SPAN OF THE JOB

(Barge Supervisor + Assistant Barge Supervisor)	2041	4
(Chief Stewards + Steward)	2041	2
(Environmental Observer + Well tester)	2041	6
(Roughneck + Roustabout)	2043	3
[J3] ((Chief Stewards + Steward) + Cook)	2043	Cont.
((Dynamic Positioning Operator + Ballast Control Operator) + (Assistant Derrickman + Motorman))	2044	5
((Driller+Assistant Driller) + (Electric Line Logging Engineer + Mudlogger))	2044	3
((Maintenance Supervisor + Assistant Maintenance Supervisor) + (Crane Operator + Assistant Crane Operator))	2044	3
((Barge Supervisor + Assistant Barge Supervisor) + (Rig Electrician + Electronic Technician))	2045	6
((Derrickman + Cement Pump Operator) + (Roughneck + Roustabout))	2046	3
(Completion Engineer + (Rig Mechanic + Rig Welder))	2046	6
(Mud Logging Supervisor + Well Test Supervisor)	2047	11
(Drilling Supervisor + Completion and Intervention Supervisor)	2047	8
((Environmental Observer + Well tester) + Subsea Engineer)	2047	4
((((Driller+Assistant Driller) + (Electric Line Logging Engineer + Mudlogger)) + ((Maintenance Supervisor + Assistant Maintenance Supervisor) + (Crane Operator + Assistant Crane Operator)))	2047	11
(Rig Superintendent + Toolpusher)	2047	8
((((Dynamic Positioning Operator + Ballast Control Operator) + (Assistant Derrickman + Motorman)) + ((Derrickman + Cement Pump Operator) + (Roughneck + Roustabout)))	2049	0
[J4] (((((Dynamic Positioning Operator + Ballast Control Operator) + (Assistant Derrickman + Motorman)) + ((Derrickman + Cement Pump Operator) + (Roughneck + Roustabout))) + (Radio Operator + Storekeeper))	2049	Cont.
((((Barge Supervisor + Assistant Barge Supervisor) + (Rig Electrician + Electronic Technician)) + ((Environmental Observer + Well tester) + Subsea Engineer))	2051	7
(Drilling Engineer + (Completion Engineer + (Rig Mechanic + Rig Welder)))	2052	6
((((Driller + Assistant Driller) + (Electric Line Logging Engineer + Mudlogger)) + ((Maintenance Supervisor + Assistant Maintenance Supervisor) + (Crane Operator + Assistant Crane Operator))) + (((Barge Supervisor + Assistant Barge Supervisor) + (Rig Electrician + Electronic Technician)) + ((Environmental Observer + Well tester) + Subsea Engineer))	2053	5
((Drilling Supervisor + Completion and Intervention Supervisor) + (Rig Superintendent + Toolpusher))	2055	3
[J5] ((((((Driller + Assistant Driller) + (Electric Line Logging Engineer + Mudlogger)) + ((Maintenance Supervisor + Assistant Maintenance Supervisor) + (Crane Operator + Assistant Crane Operator))) + (((Barge Supervisor + Assistant Barge Supervisor) + (Rig Electrician + Electronic Technician)) + ((Environmental Observer + Well tester) + Subsea Engineer))) + (Drilling Engineer + (Completion Engineer + (Rig Mechanic + Rig Welder))))	2058	Cont.
[J6] ((Mud Logging Supervisor + Well Test Supervisor) + ((Drilling Supervisor + Completion and Intervention Supervisor) + (Rig Superintendent + Toolpusher)))	2058	Cont.

these three insights, the stakeholders can effectively lay down their digitalization strategies to maximize the benefits of digitalization while minimizing socio-economic impact. Additionally, the proposed algorithm can be served as a testing platform for various “what if” scenarios, including *what will happen if we accelerate our digital readiness* and *what will happen if we relax regulatory and socio-economic constraints for someone to assume duties and responsibilities of a low skill job while holding educational and technical knowledge to do high skill jobs*.

Several critical occupations are required to successfully deploy modern technologies regardless of the industry,

process, and geographical location. For example, a recent publication of World Economic Forum [17] listed ten emerging jobs in the oil and gas sector. These jobs include data analysts and scientists, big data specialists, robotics specialists and engineers, renewable energy engineers, process automation specialists, organizational development specialists, new technology specialists, information technology services, digital transformation specialists, and scrum masters. Most oil and gas operators and service companies already have employees under these, or related, job titles. These employees generally work from a central location and work on multiple projects simultaneously. In addition to these ten occupations, it is

required to have technicians and technologists with expertise in automation, robotics, data communication and networking. With an increase in digitalization onboard offshore oil and gas platforms, additional technician/technologist jobs will be required, increasing the POB by 3~5 employees.

APPENDIX A EXISTING OCCUPATION LIST FOR OFFSHORE DRILLING INSTALLATION

Following table lists the job titles, NOC codes, McKinsey percentages (proportion of tasks that can be automated using existing technologies) and Oxford percentages (probability of automation in the next 10-20 years) for 40 occupations related to offshore drilling operations.

APPENDIX B INITIAL FEATURE VALUES AND CAREER PATHWAY COST AND RANKING MATRICES

See Tables XV–XVII.

APPENDIX C SAMPLE TIMELINE FOR JOB EMERGING AND DISAPPEARING

See Table XVIII.

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Thumeera R. Wanasinghe (Member, IEEE) received the B.Sc. (Hons.) and M.Sc. degrees in electronic and telecommunication engineering from the University of Moratuwa, Moratuwa, Sri Lanka, in 2009 and 2011, respectively, and the Ph.D. degree in electrical engineering from the Memorial University of Newfoundland, St. John's, Canada, in 2017. He was a Post-Doctoral Fellow at the Faculty of Engineering and Applied Science, Memorial University of Newfoundland, for four years, before joining the Department of Electrical and Computer Engineering, Memorial University, as an Assistant Professor (Teaching), in 2020. His research interests include distributed sensor fusion, multi-robot systems, digitalization, AI and machine learning, data science, and technological impact on the society.



Raymond G. Gosine received the B.Eng. degree in electrical engineering from the Memorial University of Newfoundland, St. John's, NL, Canada, and the Ph.D. degree in robotics from Cambridge University, Cambridge, U.K., in 1990. From 1991 to 1993, he was the Junior Chair of industrial automation at the Natural Sciences and Engineering Research Council of Canada (NSERC) and an Assistant Professor at the Department of Mechanical Engineering, The University of British Columbia, Vancouver, BC, Canada. In 1994, he joined the Faculty of Engineering, Memorial University of Newfoundland, and served as the Director for the Intelligent Systems Group, CCORE. He is currently a Professor and an Associate Vice-President Research with the Memorial University of Newfoundland, a Professor (status) with the Department of Mechanical and Industrial Engineering, University of Toronto, and a Visiting Professor with the Innovation Policy Laboratory (IPL), Munk School of Global Affairs. His main research interests include digitalization, multi-agent systems, telerobotics, machine learning, and artificial intelligence. He is a fellow of the Canadian Institute for Advanced Research (CIFAR)-Program on Innovation, Equity & The Future of Prosperity, the Canadian Academy of Engineers (FCAE), and Engineers Canada (FEC). He has served on the Board of Directors for a number of organizations and companies involved in research and technology development, including ACENET, C-CORE, Verafin Inc., and Genesis Inc., and the Chair of the Board of Directors of the Professional Engineers and Geoscientists of Newfoundland and Labrador (PEG-NL). He serves on the Registration Committee, and the Research Capacity Panel for the Government of Alberta and the Canadian Engineering Accreditation Board. He is also on the Board of Directors for Shad International and the Health Research Ethics Authority.



Bui K. Petersen received the Ph.D. degree from the Memorial University of Newfoundland, Canada, in 2018. He was a Post-Doctoral Fellow at the Faculty of Engineering and Applied Science, Memorial University of Newfoundland, Canada. He is currently an Assistant Professor with Sobey School of Business, Saint Mary's University, Halifax, NS, Canada. He has published journals, such as the *Business and Society* and the *Canadian Journal of Administrative Sciences*. His varied cross-disciplinary research examines issues related to innovation and technology, the future of work and employment, industrial relations, negotiation, conflict management, management education, organizational routines, practices, and institutions.



Peter J. Warrion graduated from the University of Waterloo and the Sloan School of Management, Massachusetts Institute of Technology. He was formerly the Research Director of United Steelworkers of America. From 1992 to 1994, he was an Assistant Deputy Minister of Finance and the Chief Economist of the Province of Ontario. He is currently a Distinguished Research Fellow with the Munk School of Global Affairs, University of Toronto. He is also the Vice-Chair of the Governing Council of Regis College, Jesuit Graduate School of Theology, University of Toronto. He leads an international research team for a joint project of the ILO and the Vatican on AI, robotics, and the future of work. He is the Chair of the Lupina Foundation and the Past Chair of the Philanthropic Foundations of Canada (PFC). His current research interests include knowledge networks, supply chains, and engineering labor markets.