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Factors Affecting Employability of Big Data Professionals: An Analysis with Special Reference to Logistics Companies in Sri Lanka

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Big Data Analytics is swiftly growing and has revolutionised the field of business, through advanced analytics. Similarly, Sri Lanka is progressively embracing big data technology, and the pioneering adopters include logistics companies. This emerging field has opened-up many employment opportunities for big data professionals (BDP). However, Sri Lanka has encountered a shortage of BDP, amidst the significant growth in the field. Thus, this study urges to analyse the factors that potentially impact the employability of BDP in the field of big data analytics, with the motive of finding solutions to reduce the skill shortage, which serves as the main objective of the research. The study was executed by analysing qualitative and quantitative data collected through a questionnaire survey followed by a series of structured interviews. The questionnaire survey was distributed among 180 employees who are currently employed in the field of big data analytics, whereas the structured interviews were carried out with 08 experts in the field. Based on the initial Exploratory Factor Analysis conducted, Education Factors, Skills and Competencies, and Job Market Factors were identified as the three main variables that affect the employability of BDP. Subsequently, a Thematic Analysis was carried out in order to investigate the impact of the aforementioned factors on the big data skill shortage, and to navigate possible remedies for it. As implications of the study, it was revealed that certain educational and competency development factors should be considered in order to diminish the skill shortage of BDP.

KEYWORDS: Big Data Professionals, Demand, Skill Shortage, Employability

INTRODUCTION

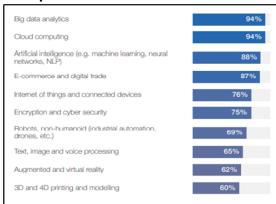
The modern world is rapidly embracing the marvels in technology. This is facilitated by the massive amounts of data generated by many sources. In the present context, data has taken a new stance called "Big Data". It is a pool of data that is massive in volume yet, growing exponentially with time. Trottier, (2014); Santoro, et al., (2018) stated that Big data which is available freely,

determines the competitive advantage of organisations which are reengineered with business process digitisation. LIRNE Asia (2017) placed the development of Sri Lanka in the spotlight of big data, stressing the importance of up-to-date and accurate data, for a developing economy.

Big data analytics is the procedure by which collections of data are analysed by Big Data Professionals (BDP) to derive useful information (Bag, et al., 2020; Najafabadi, et al., 2015). BDP includes business profiles such as Advanced Analysts, Data Scientists, Analytics Managers, Big Data Analysts etc. (The Royal Society, 2019). Big Data is a very promising field and was the top ranked new job role business leaders are planning to hire up to 2022 (World Economic Forum, 2019). Data analytics is the fastest growing sector in the field of analytics, offering employees an above average salary (Harnham Insightful Recruitment, 2017).

The study specifically relates to the field of logistics, in order to explore the shortage of BDP. This is mainly because the traditionally secluded field of logistics is one of the pioneering adopters of big data technology. Lokanathan (2018); Marikar (2018) revealed that big data is currently used in many fields in Sri Lanka including logistics, with escalating demand for professionals locally. The field of logistics is subjected to disruption, with the invasion of the field by technological advancements such as big data analytics, to recalibrate the entire sector (Irfan, 2017).

Figure 1.1: Technology Adoption in the field of logistics and transportation

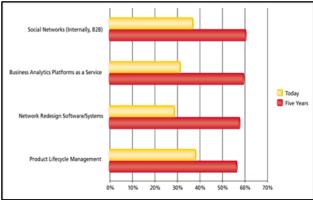


Source: World Economic Forum, (2020)

Figure 1.1 illustrates the latest statistics by World Economic Forum, regarding the technology utilisation in the field of transportation and logistics. Big data

analytics is ranked first among all the other technology enabled infrastructure, showcasing the potential of the field on logistics.

Figure 1.2: Existing and planned investment capacities for Big Data technologies



Source: BVL International, (2013)

Figure 1.2 shows the investment in Big Data in the field of logistics. It distinguishes the forecasted increase in investments within the upcoming five-year period, showing the potential impact of Big Data on the field of logistics. According to Dalsey, Hillblom and Lynn DHL, (2013), Big Data is utilised in multiple areas in the field of logistics including pickup and delivery related to customers, strategic network and operating capacity planning, last-mile and real-time route optimization, customer value supervision and risk and resilient planning. The study by Ayed (2015) mentioned that Big Data is an ideal fit for the field of logistics since it enables the systematic usage of huge sets of data from Global Positioning System (GPS) devices, vehicle sensors and customer applications which otherwise would have gone to waste.

Even though COVID-19 pandemic is a hindrance to many fields of business, experts comment that the field of Big Data has strived to find real time solutions for it. According to Haleem et al., (2020) big data technology helps in identifying the nature of the virus and finding preventive actions against it. Similarly, Agbehadji et al. (2020); Jia et al. (2020) explained that big data is heavily used to trace the contacts of infected people and their associates. FedEx is a logistics company which has utilised big data analytics to adopt its strategies in order to demand and forecast the transportation costs, during the prevailing COVID 19 pandemic (Shah & Shah, 2020).

Even though there is an increasing demand for BDP, Sri Lanka has encountered a shortage of supply of professionals to cater to this growing

demand. Similarly, World Economic Forum (2019); Part (2010); Phillips (2017); Rae (2018), examined that the job market has encountered a shortage of BDP. Similarly, Samarajiva et al. (2015); The Royal Society (2019) stated that one of the key constraints for businesses to adopt big data analytics is the shortage of skilled BDP. Even though Sri Lanka shows very promising signs regarding undertaking big data (Fuard, 2017), the skill shortage has restricted the path to excellence. Therefore, the study strives to resolve the query, "What factors would affect the employability of BDP and what remedies could be undertaken to reduce the shortage of professionals, to reach the true potential of big data analytics?"

This study becomes unique and exclusive since it strives to investigate an aspect which has not grabbed the attention of many prior researchers. At the onset, the research study intends to scrutinise the reasons for the shortage of big data skills globally and locally. Initially, the study anticipates determining the factors that affect the employability of BDP, through an Exploratory Factor Analysis. Subsequently, the analysis extended to investigate the influence of the aforementioned factors affecting the employability of BDP, by examining the present conditions of the labour market, in order to derive the most influential factor that affects the employability of BDP. The research contributes to enhancing the existing knowledge by analysing the effect of various factors on the employability of BDP. It is expected that the outcomes of the study will contribute positively to reducing the big data skill shortage in Sri Lanka and to promote the profession, emphasising its immense applications and benefits. This study will also give a summarised overview of the contribution of the Big Data skill force during COVID-19 pandemic situation.

LITERATURE REVIEW

Ohlhorst (2013) expressed that big data is undertaken by many companies in the world as a main source of competitive advantage.

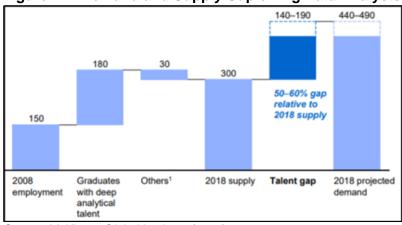
Figure 2.1: Forecasted demand of the data science and big data analytics workforce by 2020

Economy	Current DSA Workers	Projected DSA Workers Needed	Percent Change
Malaysia ²⁴	4,000 (2016)	20,000 (2020)	400%
The Philippines ²⁵	147,420 (2016)	340,880 (2022)	131%
Singapore ²⁶	9,300 (2015)	15,000 (2018)	61%
Canada ²⁷	33,600 (2016)	43,300 (2020)	33%
United States ²⁸	2,350,000 (2015)	2,720,000 (2020)	16%

Source: Pompa, et al., (2017)

Figure 2.1 emphasises that the big data skill shortage is linked to the demand for professionals. Even though the demand for BDP is rapidly increasing, the job market has encountered a significant gap in BDP, implying that the supply of professionals to the job market is poor, even though they are in high demand.

Figure 2.2: Demand and Supply Gap of Big Data Analysts in US, 2018



Source: McKinsey Global Institute, (2011)

Figure 2.2 shows the forecasted gap in-between the supply and demand of BDP in the US, for the year 2018. Based on that, the projected demand is much higher than the forecasted supply, resulting in a shortage in big data skills of 50%-60%.

39% 39% 34% 31%

Big data/ Cyber security Artificial Enterprise Business analysis

Figure 2.3: Top 05 most scarce skills

Source: Harvey Nash/ KPMG CIO, (2019)

Figure 2.3 shows that big data analytics is the scarcest skill in the global corporate field. Wegner & Kückelhaus (2013) elaboratively mentioned that Big Data is an untouched asset which can be successfully exploited by companies once they undergo a paradigm shift in mindset as well as infrastructure. As shown in Figure 2.4, the market size of big data is expected to grow at a rapid rate.

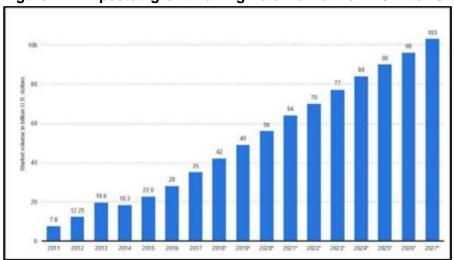


Figure 2.4: Expected growth of Big Data Market from 2011 to 2027

Source: Columbus, (2017)

Right human skill is critical in big data analytics (Dubey et al., 2019; Wamba et al., 2017). According to SHRM, (2016), 59% of organisations expect to elevate the job positions which require the skill of data analysis from 2017-2021.

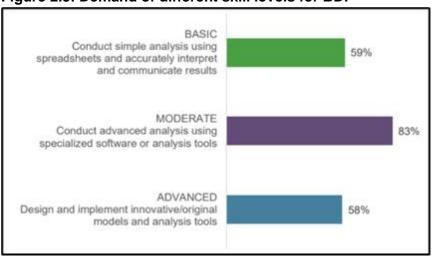


Figure 2.5: Demand of different skill levels for BDP

Source: SHRM, (2016)

Figure 2.5 interprets different skill levels required by employees. The analysis revealed that 60% of the organisations demand BDP with the ability to interpret and communicate results.

Education and subject related knowledge are core factors anticipated by employers, when recruiting BDP. Gibson (2017); Kalota (2015) explained that employees' understanding of big data analytics, adds value to organisations.

DASCA, (2020) is a pioneering credentialing body for the data science profession. SAS, (2020) is an international institute which offers certification to BDP, which is a value addition for them in career progression. In the long run, the recognized professional bodies collaboratively assess the quality of the accreditations, in order to uplift the standard of data related programs and platforms (The Royal Society, 2019).

The time duration of higher educational qualifications plays a significant role since it gives a gist of the quality and capacity of the specific qualification.

Table 2.1: Time duration of Undergraduate and Postgraduate Big Data related programs in Sri Lankan public and private Universities

Type	Name of the University/Institution	Academic Program	Time Duration
Public	University of Moratuwa	Postgraduate certificate in data analysis and pattern recognition	1 year
	University of Colombo School of Computing (USSC)	Master of Business Analytics	2 years
Private	Informatics Institute of Technology (IIT)	BSc (Hons) Artificial Intelligence and Data Science	4 years
	Sri Lanka Institute of Information Technology (SLIIT)	BSc (Hons) in Information Technology Specializing in Data Science	4 years
	National Institute of Business Management (NIBM)	BSc (Hons) Data Science	3 years
	National Institute of Business Management (NIBM)	Advanced Diploma in Data Science	1 year
	NSBM Green University Town	Professional Diploma in Data Science	1 year

Sources: IIT, (2020); NSBM, (2020); SLIIT, (2020); UOM, (2019); USSC, (2020)

The time durations of local undergraduate and postgraduate programs relating to big data and advanced analytics are indicated in Table 2.1. It shows that even though most undergraduate programs are offered for three-four years, almost all postgraduate programs are conducted for a shorter duration.

International educational platforms for big data analytics, such as Pearson and Lytics Labs facilitate mainstream physical or virtual learning of various modules (Williamson, 2017). The Data Skill Taskforce is a UK based establishment which encourages data skills and ethical practices of main institutions. There are new forms of hybrid education and apprenticeships emerging in the field of work related to data (Blake, 2019).

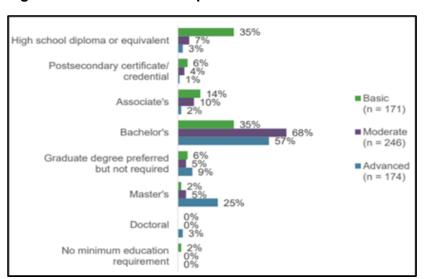


Figure 2.6: Educational Requirement at each level of recruitment

Source: SHRM, (2016)

Figure 2.6 is a breakdown of the big data workforce, according to their educational qualifications. Even though most entry level requirements are just a diploma, it is very critical to pursue bachelor's, master's and PhD studies when climbing up the corporate ladder.

IBM Data Science Professional Certificate is a platform which offers a vivid range of courses for professional BDP, which can be pursued independently even while engaging in employment (Widjaja, 2019). University of Oxford, along with the University of Harvard, are offering short term professional courses for BDP (Dhawan & Zanini, 2014). Samarajiva et al. (2015) mentioned that LIRNEasia, which is a Sri Lankan policy regulation institution in the field of ICT, has demonstrated the value of big data. Apart from the traditional academic platforms, many MOOCs (Massive Open Online Courses) and boot camps are launched in the field of Big Data (Burtch Works, 2018).

Hetherington (2019) mentioned that the field of data science and advanced analytics is inherently multidisciplinary and includes statistics, mathematics, data and computational research. Sedkaoui (2018) expressed that BDP requires brilliant analytical skills, with a capacity to comprehend, manipulate and interpret data. DHL, (2013) emphasised that the key to successful Big Data implementation in companies is a remarkable workforce with exceptional skills. Similarly, Bag et al. (2020) emphasised that the

technological and managerial competencies of BDP are brought about through their talent capabilities, which are crucial in the path to success.

Park City Math Institute (2016) prioritised communication skills as a core competency for Big Data graduates. This is mainly because the findings of data analytics should be effectively communicated by BDP to superiors, team members and also the general public. The study also emphasised the importance of group analytics and presentation skills for a Big Data graduate.

Ohlhorst (2013) stated in his study that BDP should not only have technical skills but they should be well-nurtured by business skills as well. Big Data strives to harmonise a synergistic approach to solve organisational problems and enable effective decision making (Park City Math Institute, 2016). The study also describes the significance of exposing BDP to ethical approaches in data security, data privacy, transparency and professionalism concerns, which are compelling areas in the current context.

However, the study by Ajah & Nweke (2019) revealed that many organisations are not sufficiently equipped with the knowledge and skill to implement big data analytics or to interpret the results of it. Therefore, it suggested the importance of building an organisational culture oriented on analytics by bridging this skill and knowledge gap. With the outbreak of the COVID-19 pandemic, most companies are shifting to business process digitization. Based on this, Harvey Nash/ KPMG CIO, (2020) revealed that 35% of employers are anticipating transforming the workforce to polish their technology-related competencies. Most companies take a strong stance on uplifting their financial and operational performance by adopting big data analytics (Duan, et al., 2019; Dwivedi et al., 2019; Dwivedi et al., 2017; Swink & Srinivasan, 2017)

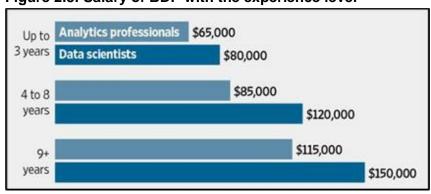
Figure 2.7: Workforce entry by prior experience

DSA Framework Category	Postings Requesting Experienced Workers (at least 3 Years Prior Work Experience)
All	81%
Data-Driven Decision Makers	88%*
Functional Analysts	71%
Data Systems Developers	84%
Data Analysts	76%
Data Scientists & Advanced Analysts	78%
Analytics Managers	94%*

Source: Columbus, (2017)

According to Figure 2.7, more than 76% of employers anticipate recruiting experienced BDP. The study of Park City Math Institute (2016) stated that "Capstone projects" should be a mandatory component of the experience and internship programs for Big Data employees since it strives to polish the problem solving, critical thinking, teamwork, communication and research skills of employees.

Figure 2.8: Salary of BDP with the experience level



Source: Waller, (2014)

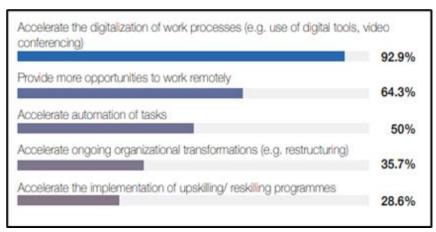
Based on Figure 2.8, as the experience grows, the remuneration of the big data employees increases. Thus, it further emphasises the significance and importance of prior industry experience for BDP.

Blake (2019) claimed that the field of data sciences is a very gratifying career which is increasingly relied upon by society. The study of Burtch Works LLC, (2018) stated that due to the increasing recognition of the field, many professionals from other business fields tend to shift towards the field of Big Data, undergoing a career change, leading to a continued escalation in the pool of talent.

Aryal et al. (2018); Cao (2017); Columbus (2017); Wamba et al. (2019) showed that embracing big data technology in organisations requires high level software like Hadoop, Apache Pig and database management systems –NoSQL. In addition, Song (2016) mentioned that tools such as IBM Watson Analytics and other automated software will instil a remarkable effect on the process of training BDP, to achieve better in their career.

The extensive utilisation and exchange of data followed by the strive for innovation has paved the way to an interdisciplinary workforce enriched with unique, novel and emerging skills and competencies (The Royal Society, 2019).

Figure 2.9: Impact of COVID-19 pandemic on logistics and transportation companies



Source: World Economic Forum, (2020)

Figure 2.9 is a representation of different strategies that global logistics companies follow to adapt to the "New Normal", post COVID-19. Most companies have considered work process digitalization as the most viable option, creating space for big data and other advanced analytics platforms to revolutionise the field of logistics. Similarly, certain companies have also started initiatives to upskill and reskill the current employees, in order to move forward with the digitalization of business processes. These practices

enhance the potential of growth and further integration of fields of logistics and big data, empowered by the nurturing of a skilled workforce.

METHODOLOGY

The research onion (Figure 3.1) which was developed by Saunders et al. (2009) explains the stages to be followed when developing a research strategy.

Positivism Philosophies Experiment Deductive Survey Approaches Mono method Realism Cross-sectional Strategies Mixed Action collection methods research and data Choices analysis Grounded Longitudinal theory Time Multi-method horizons Ethnograph Interpretivism Inductive Archival research Techniques and procedures

Figure 3.1: Research Onion

Source: Saunders et al., (2009)

This study is conducted based on Pragmatism. Vallack (2010) explained that this philosophy is ideally used for research studies conducted based on a mixed method. The study began with a qualitative notion of inquiry and qualitative data facilitates to assess the current demand for big data professionals while the quantitative method is useful in establishing the relationships.

An inductive approach is selected based on the layout and execution of the research study.

The study involves the use of structured interviews and questionnaire surveys as its research strategies to collect qualitative and quantitative data. Quantitative data is used for statistical analysis. Meanwhile, qualitative data

is utilised to draw conclusions based on underlying relationships. Thus, this study adopts a mixed method.

This study uses a cross sectional approach, where the information is gathered at a particular point in time.

Population

The target population for the series of structured interviews is the experts in the field of Big Data, in the Colombo District. Since the experts in the field of Big Data are unknown, the population of the study is also unknown. The respondents for the questionnaire survey are employees of selected logistics companies in the Colombo District.

Sample

In order to collect data for the questionnaire survey, the sample size of 180 operational and management level respondents in the field of technology are requested to participate to fill out a questionnaire. The sample size was determined by the use of the rule of thumb method and convenience sampling method used to collect data under non-probability sampling technique. Structured interviews were conducted with selected industry experts in the field of Big Data, and the sample size was decided by locating the saturation point after investigating the responses.

Exploratory Factor Analysis

This research is a salient collaboration of big data analytics, which is a heavily technical aspect, with the availability of proper human resources in the field. It is a very unique study and it explores an area which has not been overlooked by many prior researchers. Thus, the researchers lacked firm theory and substantial models to support the conceptual framework in order to develop hypotheses. Therefore, an Exploratory Factor Analysis was conducted at the beginning in order to determine the factors which affected the employment of BDP.

Determining the factors

The researchers initially determined certain indicators that would possibly be affecting the employment of professionals in the field of big data analytics. Those indicators were chosen randomly based on the literature survey. The aforementioned indicators include Competency of Employees, Academic

Knowledge, Higher Educational Qualifications, Remuneration, Experience, Soft Skills, Managerial Skills, Orientation of Qualifications, Professional Qualifications, Existing professionals in the field, Recognition, Infrastructure, Accreditations, Professional Networks and Time Duration.

Data Collection

Based on the indicators identified by the researchers, a questionnaire was developed and circulated among the employees in the field of big data analytics, who are currently employed in local logistics companies. The researcher considered the responses of 180 operational and managerial level employees in order to conduct the Exploratory Factor Analysis.

Preparation of data for analysis

Removing outliers

Based on the data collected, there were four potential outliers have been excluded from the dataset, as shown in Table 4.1.

Table 4.1: Data Screening

Questionnaire responses collected	180
Questionnaires discarded	26
Questionnaires considered	154
Outliers Removed	04
Questionnaires utilized	150

Source: Sample Survey (2020)

Table 4.2: Guidelines for KMO Values

Indicator	Value
Poor	<0.5
Average	0.5 - 0.6
Acceptable	0.6 - 0.7
Good	0.7 - 0.8
Excellent	>0.8

Source: Hutcheson & Sofroniou, (1999)

Table 4. 3: KMO Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.693
Bartlett's Test of Sphericity	Approx. Chi-Square	502.064
	Df	78
	Sig.	.000

Source: Sample Survey (2020)

According to Table 4.3, the output indicates that KMO sampling adequacy value is 0.693, which is considered as an acceptable value according to Hutcheson & Sofroniou (1999). The matrix can be ruled out if the Sig. Value of the test is less than 0.005 (Field, 2000; Pallant, 2013). Therefore, since the Sig., Value in Bartlett's Test of Sphericity is less than 0.005, the data set is adequately sampled.

Principal Component Analysis

A Principal Component Analysis (PCA) was conducted in order to distinguish the factors affecting employment of BDP. According to the initial analysis conducted, Higher Educational Qualifications, Academic Knowledge and Remuneration were identified as three doubtful indicators. This was because their communality value was below 0.3 and the value in the component matrix was less than 0.5. If the communality value is less than 0.3, then it means that only less than 30% of the variance in this indicator shares a common origin with others. Therefore, those indicators should be excluded from the analysis (Hadi, et al., 2016). The component matrix displays the factor loadings without rotating the variables. If it contains any indicator less than 0.5, then the impact of that indicator on that specific variable is considered to be negligible.

After filtering those three indicators, the same Principal Component Test was carried out. Then the researchers considered the output of the "Total Variance Explained" in Table 4.4.

Table 4. 4: Total Variance Explained

Comp onent	In	itial Eigenva	alues	Extrac	ion Sums of Loadings		Rota	tion Sums of S Loadings	Squared
	Total	% of Vari ance	Cumu lative %	Total	% of Vari ance	Cumu lative %	Total	% of Variance	Cumu lative %
1	2.953	24.607	24.607	2.953	24.607	24.607	2.471	20.595	20.595
2	2.357	19.641	44.248	2.357	19.641	44.248	2.174	18.120	38.715
3	1.344	11.198	55.447	1.344	11.198	55.447	2.008	16.732	55.447
4	1.077	8.972	64.419						
5	.879	7.328	71.748						
6	.722	6.016	77.763						
7	.664	5.535	83.298						
8	.563	4.689	87.988						
9	.453	3.771	91.759						
10	.372	3.101	94.860						
11	.335	2.792	97.652						
12	.282	2.348	100.000						

Source: Sample Survey (2020)

Table 4.4 revealed that 55.47% of the total variances were achieved from the first three factors collectively. It indicated that 03 independent variables could be determined by clustering all the indicators into three main categories. However, the fourth indicator also showed a value greater than one. Therefore, a parallel analysis was conducted in order to verify the total number of variables.

Table 4.5: Parallel Analysis

Component Number	Eigenvalue from the PCA	Parallel Analysis Value	Final Decision
1	2.953	1.519	Accept
2	2.357	1.386	Accept
3	1.344	1.281	Accept
4	1.077	1.192	Reject

Source: Sample Survey (2020)

The parallel analysis in Table 4.5 shows how the number of variables was determined to carry out factor extractions. In this process, the Eigenvalues obtained from PCA were compared with the Eigenvalues generated by Patil et al. (2017). The two values were compared in a way that if the Eigenvalue

generated from PCA was greater than that of the parallel analysis, then the indicator was accepted (Horn, 1965).

After determining the number of independent variables for factor extractions, then the factors were rotated for further analysis. The main motive behind factor rotation is to align them in a way which makes it more convenient for interpretations.

Table 4.6: Rotated Component Matrix

	(Componer	nt
	1	2	3
Existing professionals	.786		.185
Recognition in the local job market compared to foreign job market	.756		
Adoption of new infrastructure	.686		.118
Effect of industry experience	.643		
Professional networks	.596		
Presence of sufficient local qualifications		.827	.230
Crash courses to be completed in less time		.804	.204
Accreditation body provide guidance	.131	.636	.215
Professional qualifications		.611	126
Effect of business and managerial skills		.130	.827
Satisfaction level of local graduates compared to foreign graduates			.801
Effect of soft skills		.148	.691

Source: Sample Survey (2020)

Based on the Rotated Component Matrix in Table 4.6, the researchers loaded the factors to three main variables. The factor loadings were done so that the factors with a value of more than 0.5 are grouped into categories based on their orientation.

Table 4.7: Labelling Factors

Factors	Labelled Factors	Indicators	Factor Loadings
01	Job Market Factors	Existing Professionals	.786
	. 40.0.0	Recognition	.756
		Infrastructure	.686
		Experience	.643
		Professional Networks	.596
02	Educational Factors	Orientation of Qualifications	.827
	1 401010	Time Duration	.804
		Accreditations	.636
		Professional Qualifications	.611
03	Skills and Competencies	Managerial Skills	.827
	20	Competency of Graduates	.801
		Soft Skills	.691

Source: Sample Survey (2020)

The researchers labelled the factors based on the composition of indicators in them. This was based on developing the conceptual framework for the study.

Normality

Table 4.8 shows the normality measures of the data set of the research study.

Table 4. 8: Skewness and Kurtosis

	Education Factors	Skills and Competencies	Job Market Factors
Skewness	187	613	403
Std. Error of Skewness	.198	.198	.198
Kurtosis	208	.119	267
Std. Error of Kurtosis	.394	.394	.394

Source: Sample Survey (2020)

Rose et al. (2015) mentioned that if the standard error of skewness and Kurtosis are within the range of +1.96 and -1.96, then the data set is normal. Since the standard errors of the data set shown in Table 4.8 are in between this range, it can be concluded that it is normal.

Testing for Validity and Reliability

The researchers utilised the Expert Validity technique since the relationship between variables are yet unknown until the Exploratory Factor Analysis is conducted.

The reliability test is done by getting Cronbach's alpha value in SPSS. Bernstein, (1994) confirmed that the standard value for Cronbach's alpha could be more than 0.6, which Bagozzi R.P. (1988) previously recommended. Table 4.9 represents the reliability values of each variable utilised in this research study along with the number of indicators in each variable.

Table 4. 9: Reliability for each variable

Variable	Cronbach's Alpha	No of Items
Educational Factors	.715	4
Skills and Competencies	.620	4
Job Market Factors	.718	6
Employment	.644	3

Source: Sample Survey (2020)

Testing for Multicollinearity

Table 4. 10: Multicollinearity

	Tolerance	VIF
Education Factors	.961	1.040
Skills and Competencies	.994	1.007
Job Market Factors	.899	1.112

Source: Sample Survey (2020)

If the tolerance value of the variables exceeds "one", then there is no multicollinearity between the variables. However, if this value equals "zero", then the variables show perfect multicollinearity. Therefore, based on Table 2.10, the variables considered in the study are proven to have no multicollinearity. The acceptable range of VIF value is between 10 and 0.1 (Field, 2005). The variables of the study abide by this rule as well. Hence, it shows that there is no multicollinearity prevailing among the variables.

Descriptive Statistics

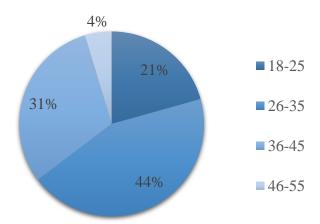
Demographic profile

The 150 respondents were categorised into five groups under different age levels as 18-25, 26-35, 36-45, 46-55, 56 and above. Among them, the age group between 26-35 represented the majority (44%) of respondents. Many of these respondents are enriched with more than three years of working experience, hence could be currently in the initial stages of career progression. The second highest rate was recorded from 36-45 age category. which amounted to 31%. The majority of the respondents of this age category might be employed in higher executive positions in the organisational hierarchy with a good experience in the field. The third highest rate was recorded by employees at the age limit 18-25, which summed up to 21%. It could be assumed that many of the respondents in this age group are newly recruited to the company or in their probationary period. Finally, the least responses were recorded from the age group 46-55, accounting for 4% of the total respondents. Furthermore, there are no responses recorded from the 56 and above age category. This gives an indication of the novelty of the field of big data. Since only a very few respondents above the age of 46 have responded to the questionnaire, it could be assumed that the field of big data is not much embraced by the employees belonging to that age limit. However, the high response rates from early and mid-career professionals show their interest and involvement in the field of big data analytics (Figure 4.1).

Figure 4. 1: Age

Source: Sample Survey (2020)

When considering the Highest level of education, only 7% of the respondents



belonged to the category of PhD, depicting that there are very few professionals in the field of big data analytics locally who have completed their Doctor of Philosophy in the same field. The highest percentage of respondents are in the group who have completed their Bachelor's Degree (55%). Second highest category includes the employees who have acquired Professional Qualifications from the field of big data analytics. It is represented as a percentage of 20%. The successive highest category of respondents is from the BDP who have completed their Master's Degree. The employees who have completed Post Graduate Diplomas in big data analytics amount to 18%. As Figure 4.2 demonstrates, all the respondents have acquired more qualifications than Advanced Level.

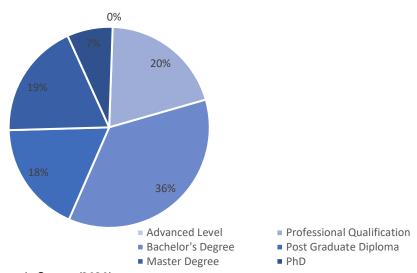


Figure 4. 2: Highest Educational Qualification

Source: Sample Survey (2020)

The researchers further analysed whether the respondents had acquired their highest educational qualification from a local or a foreign University/institution. Among the 150 respondents, the majority have acquired their highest educational qualification from foreign Universities/institutions, and it amounts to 52%. The are 48% of employees have acquired their highest education qualification locally, which is comparatively less than graduates from foreign Universities. This demarcates the lack of higher educational platforms for BDP locally. Figure 4.3 shows the orientation of the educational qualifications of respondents based on the country and region.

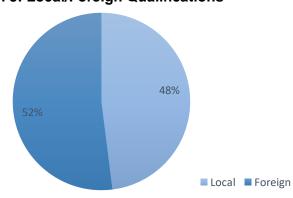
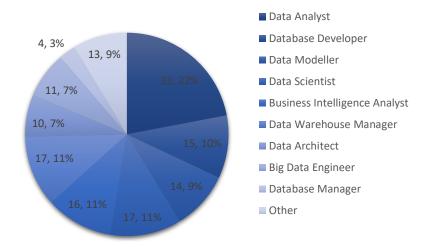


Figure 4. 3: Local/Foreign Qualifications

Source: Sample Survey (2020)

Based on Figure 4.4, the majority of the respondents were data analysts, which summed up to a percentage of 33.22%. Both data scientists and data warehouse managers represented 17.11% each, which was the second highest. Business intelligence analysts, database developers, data modellers and other professionals have also responded to the survey. There are 11.7% of big data engineers along with 10.7% of data architects. Meanwhile, the respondents include only a very lesser number of database managers.

Figure 4. 4: Job Profile



Source: Sample Survey (2020)

In order to analyse the most commonly utilised software in Sri Lanka, five main types of software which are commonly used by BDP are considered, and the respondents rated them based on their level of utilisation. According to Figure 4.5, most professionals heavily utilise Apache Spark, while Hadoop is ranked second based on high usage. Meanwhile, Hadoop and Apache Spark are utilised mostly in the moderate usage category as well. Cassandra and Tableau are rated as low usage software by the respondents. Cassandra is the software that many respondents have rated as "no usage" as well.

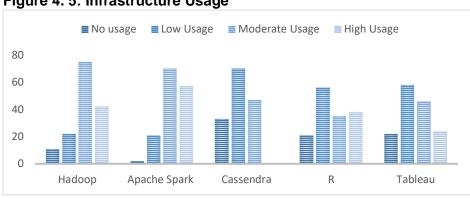


Figure 4. 5: Infrastructure Usage

Source: Sample Survey (2020)

Researchers intended to analyse the impact of the COVID-19 pandemic on big data employees. Based on their responses, most companies have initiated teleworking platforms due to the "New Normal" culture in the business sector. This was mentioned by 47% of the respondents, which summed up to be the highest impact on the field from the pandemic. 36% of the employees have mentioned that they have been introduced to flexible working hours such as flexed time and roster plans. 13% of the respondents have commented that all the traditional big data related platforms were transferred to the cloud so that the employees could remotely access the databases. Based on Figure 4.6, only a few numbers of employees experienced salary cut downs. This implies that the COVID-19 has very slightly impacted the field in a negative manner.

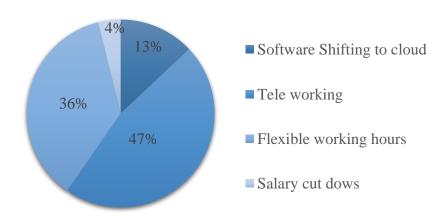


Figure 4. 6: Impact of COVID-19

Source: Sample Survey (2020)

Thematic Analysis

The research study employs thematic analysis to review and analyse qualitative data collected through a series of structured questionnaires.

Initial Reading of Texts

Braun & Clarke (2012) explained that this initial step is very vital to understand the content and the basic idea derived from various aspects. In this research study, the interviews conducted with experts in the field of big data were initially transcribed. Then they were reviewed by the researchers in order to understand the true narration of the respondents.

Coding the Texts after Repeated Reading

The interview texts are repeatedly read in order to absorb the true message delivered through them. According to Attride-Stirling, (2001); Braun & Clarke (2006); Lincoln & Guba (1985), each consecutive reading enhances the scope of vision of the researchers, and by doing so, they will be able to create as many codes as possible from the given data set. In this phase, the transcribed interviews were extensively analysed, by comparing the similarities and differences between each other in order to determine the codes. The researchers generated 108 basic codes after the comprehensive analysis of the responses.

Generating Themes through Codes

The concept behind the generation of themes is the process of consolidation of the codes into like groups (Attride-Stirling, 2001; Braun & Clarke, 2006; Lincoln & Guba, 1985). In order to generate themes for this study, the researchers carefully analysed all the codes generated and divided them into groups initially based on their common characteristics. Those categories served as the bases for developing themes covering up a few individual variables each. The final result obtained by the researchers included three main themes called Educational Factors, Skills and Competencies and Job Market Factors. Apart from that, another two codes; namely, Importance of Big Data in Logistics and Impact to the field of COVID-19, were separately considered by the researchers, based on their significance to the field.

The Table 5.1 is a presentation of data that the researcher coded initially along with the themes generated through them.

Table 5. 1: Code Structures

Importance of Big Data in Logistics	C01, C15, C29, C42, C55, C69, C83, C96 C02, C16, C30, C43, C56, C97 C02, C16, C30, C56, C97 C43, C84
* High * Moderate * Low Educational Factors • Accreditations • Local * Ample * Scarce • Foreign * Ample * Scarce • Time Duration * Have Crash Courses • Local/Foreign Qualifications * High local standard	C83, C96 C02, C16, C30, C43, C56, C97 C02, C16, C30, C56, C97 C43, C84
* Low Educational Factors • Accreditations • Local * Ample * Scarce • Foreign * Ample * Scarce • Time Duration * Have Crash Courses • No Crash Courses • Local/Foreign Qualifications * High local standard	C02, C16, C30, C43, C56, C97 C02, C16, C30, C56, C97 C43, C84
* Low Educational Factors • Accreditations • Local * Ample * Scarce • Foreign * Ample * Scarce • Time Duration * Have Crash Courses • No Crash Courses • Local/Foreign Qualifications * High local standard	C02, C16, C30, C56, C97 C43, C84
Educational Factors	C02, C16, C30, C56, C97 C43, C84
Accreditations Local * Ample * Scarce Foreign * Ample * Scarce Time Duration * Have Crash Courses No Crash Courses Local/Foreign Qualifications * High local standard	C02, C16, C30, C56, C97 C43, C84
 Local Ample * Scarce Foreign Ample * Scarce Time Duration Have Crash Courses * No Crash Courses Local/Foreign Qualifications High local standard 	C02, C16, C30, C56, C97 C43, C84
* Ample * Scarce • Foreign * Ample * Scarce • Time Duration * Have Crash Courses * No Crash Courses • Local/Foreign Qualifications * High local standard	C02, C16, C30, C56, C97 C43, C84
* Scarce • Foreign * Ample * Scarce • Time Duration * Have Crash Courses * No Crash Courses • Local/Foreign Qualifications * High local standard	C02, C16, C30, C56, C97 C43, C84
Foreign * Ample * Scarce • Time Duration * Have Crash Courses * No Crash Courses • Local/Foreign Qualifications * High local standard	C02, C16, C30, C56, C97 C43, C84
* Ample * Scarce • Time Duration * Have Crash Courses * No Crash Courses • Local/Foreign Qualifications * High local standard	C43, C84
* Scarce • Time Duration * Have Crash Courses * No Crash Courses • Local/Foreign Qualifications * High local standard	C43, C84
Time Duration * Have Crash Courses * No Crash Courses Local/Foreign Qualifications * High local standard	·
* Have Crash Courses * No Crash Courses • Local/Foreign Qualifications * High local standard	000 004 005 000
* No Crash Courses • Local/Foreign Qualifications * High local standard	000 004 005 000
 Local/Foreign Qualifications * High local standard 	C03, C31, C85, C98
* High local standard	C17, C44, C57, C71
r ligit local standard	
* High foreign standard	C58, C72
	C04, C18, C32, C45, C58, C86, C99
Professional Qualifications	
 Local 	
* Ample	
* Scarce	C05, C19, C33
Foreign	
* Ample	C05, C19, C33, C73, C87, C100
* Scarce	
Skills and Competencies	
 Soft Skills 	
* Important	C06, C20, C34, C46, C60, C74,
	C88, C101
* Unimportant	

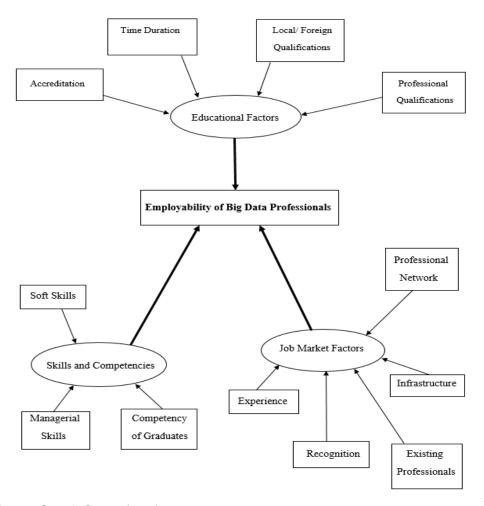
•	Manag	jerial Skills				
	*	Important	C07, C21, C35, C61, C75			
	*	Unimportant	C47, C89, C102			
•	Competency of Graduates		C36, C62, C90, C103			
	*	Ample competency				
		development programs				
	*	Less competency	C08, C48, C76			
		development programs				
	*	No competency	C22			
		development programs				
Job Mar	Job Market Factors					
•	Experi	ence				
	*	Important	C09, C23, C37, C49, C63, C77, C91, C104			
	*	Unimportant				
•	Recognition					
	*	High				
	*	Moderate	C105			
	*	Low	C10, C24, C38, C50, C64, C78,			
			C92			
Existing Professionals						
	- 1	Number				
	*	High				
	*	Moderate				
	*	Low	C11, C65, C79, C106			
	• E	Expertise and Knowledge				
	*	High	C51			
	*	Low	C25			
Infrastructure						
	*	Constantly updated	C12, C26, C52, C66, C80, C93			
	*	Not constantly updated	C39			
Professional Networks						
	*	Important	C13, C27, C40, C53, C67, C81,			
			C94, C107			
	*	Unimportant				
Impact to the field from COVID-19						
	*	Positive	C14, C28, C68, C95			
	*	Negative	C41, C108			
	*	No impact	C54, C82			
Source: Sc	amala C	Survey (2020				

Source: Sample Survey (2020

Thematic Network

The thematic network shown in Figure 5.1 was developed by the researchers by investigating the codes developed through the interview texts.

Figure 5. 1: Thematic Network



Source: Sample Survey (2020)

Data Analysis

The data analysis is conducted by analysing the themes and codes generated by the researcher.

Importance of Big Data in the field of Logistics

All the respondents agree that big data is perfectly compatible with the field of logistics. They placed the value of big data for the field of logistics in the "High" category, since it is a unique yet valuable integration of two fields. Many respondents justified their argument, saying that big data is already acclimatised in many logistics giants such as DHL and UPS. According to Respondent eight, the massive amount of data received by supply chain logistics is utilised to implement big data analytics.

Educational Factors

Accreditation

Based on the comments of the respondents, many have agreed that there are no recognised accreditation bodies locally. However, 63% of the respondents have commented that there are ample recognised accreditation bodies for big data professionals globally. Adding to this, Respondent eight has stated that there are recognised accreditation bodies for BDP, such as DASCA, IOA and CAP by Informs. Conversely, Respondent four and Respondent seven have brought about a contradictory argument saying that there are only a limited number of accreditations internationally as well.

Time Duration

Half of the respondents commented that there are crash courses for BDP. Justifying this, Respondent seven has said that there are online platforms like Coursera. Meanwhile, Respondent eight has also said that there are online crash courses offered by IBM and Google. Conversely, the remaining 50% of the respondents have commented that there are no crash courses for the employees in the field of big data analytics.

Orientation of Qualifications

This indicator investigates the standard of local qualifications in comparison to foreign qualifications. Respondent five and respondent six have commented that the standard of local graduates who graduate from local Universities is high when compared to foreign graduates. However, the majority of the respondents have stated that the quality and standard of foreign qualifications are high when compared to local qualifications. Respondent five has implied that both local and foreign qualifications are standardised, but from different perspectives. He has expressly mentioned that local graduates have more capacity to work than foreign graduates, but foreign graduates prioritise the quality of work rather than quantity.

Professional Qualifications

Three Respondents have commented that professional qualifications are scarce in the local context. The majority of the respondents have agreed that there are ample professional qualifications available for BDP internationally. Respondent one has mentioned Udemy and Coursera as examples in order to justify her point of view. Respondent two, respondent three and respondent six have commonly mentioned AWS as a recognised professional qualification. Respondent seven has given multiple examples such as Cloudera, Hortonworks, Elasticsearch, AWS, Azure, Cloud, Datadog and Snowflakes.

Skills and Competencies

Soft Skills

All the respondents have commonly expressed that soft skills are very important for BDP. They have specifically said that communication is the most important skill since it enables the professionals to express their findings to the top management and to the clients. Respondent two has given a different point of argument, saying it is very critical for a big data employee to manage the stakeholders throughout the day. Therefore, he should possess collaborative skills for that.

Managerial Skills

The majority of the respondents have agreed that managerial skills are critical for BDP. Justifying this, many respondents have collectively stated that people handling, time management, cost management, critical thinking and project management skills are vital for BDP. Respondent seven stated that the chance that people will try to cheat will reduce if big data employees have knowledge of managerial aspects as well. However, respondents four, seven and eight have mentioned that it is not very critical for big data employees to possess managerial skills since they engage in a technical role rather than a managerial role.

Competency of Graduates

Four respondents have stated that many companies implement ample competency development programs for employees in the field of big data. Respondent seven has interestingly mentioned that even though his company extends training and development programs for BDP, they mostly expect the employees to be self-taught. Respondents one, four and six mentioned that there are only a lesser number of competency development programs for

BDP in local companies. Respondent four has justified his viewpoint saying that his company conducts competency development programs only catering to the specific requirements of employees. Also, Respondent six has stated that the company he is employed in has newly initiated training and development programs for BDP. However, respondent two has strongly mentioned that there are no competency development programs for BDP as at now.

Job Market Factors

Experience

All the respondents have commonly agreed that level of experience is a major factor affecting the employment of BDP. Respondents one and five have mentioned the importance of experience in driving the performance and career progression of an employee. Respondent two stated that experience boosts the confidence of BDP, whereas respondent six has mentioned that the knowledge of BDP should be up-to-date even though they have a very high experience level.

Recognition

The researchers identified that the majority of the respondents' opinion was that big data analytics as a profession is not yet recognised in Sri Lanka. According to Respondents one, three, four, five and seven, the field is still in the emerging stage, which is the main cause for the lack of recognition. Respondent two has captivatingly mentioned big data analytics as a "Surprise Field". However, respondent eight has a different opinion regarding the recognition of the profession. He states that it is moderate in recognition since it is growing at a rapid rate.

Existing Professionals

Based on the responses received, respondents one, six and seven have mentioned that the number of existing professionals in the field locally are very less. Meanwhile, respondent two has mentioned that the existing professionals have so much to improve when compared to foreign professionals. However, respondents four and five have given contradictory thoughts regarding this, saying that existing professionals are knowledgeable. Respondent four has specifically given an interesting comment saying if the elderly people retire soon then the hindrances for the young professionals to grow and develop will be less. Meanwhile, respondents three and seven have not specifically mentioned anything about this factor.

Infrastructure

The majority of the respondents have stated that most companies in Sri Lanka constantly update their infrastructure related to big data analytics. Respondent two has stated that three main factors should be looked into when updating the existing infrastructure. They are the cost, the number of cases that can be captured and the type of data collected. Meanwhile respondent five has stated that big data related infrastructure should be compatible with other software used in the company. Meanwhile, respondent six stated that their company conducts a lot of research on the latest developments in infrastructure. However, respondent three has given a contrary opinion saying that local companies do not regularly update their infrastructure.

Professional Networks

All the respondents have commented that professional networks are of utmost importance to employees in the field of big data. Many have justified their opinions by saying that their networks help them immensely as advice and knowledge sharing platforms.

Impact of COVID-19 to the field of Big Data Analytics

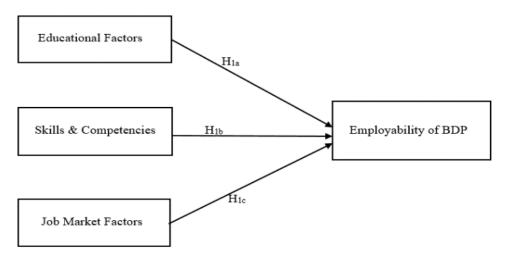
Four respondents have said that there is a very high positive impact between the two. According to the respondents, one and two, big data is used in suspect detection, when it comes to mitigating the effect of the pandemic. Respondent two stated that "It would be more appropriate to analyse the impact of Big Data to COVID-19, rather than considering the other way round", emphasising the important role that big data plays during the current pandemic. Meanwhile, respondent five said that their company utilises big data in order to track consumer behaviour and deliver items to households efficiently, during lockdown periods. Respondents three and eight have mentioned that the impact of COVID-19 on the field is negative. This is because of reasons such as cutting down investments in the field and risks of data divulging due to teleworking. However, respondents four and six have stated that there is no specific impact of the pandemic on the field of big data.

DISCUSSION AND CONCLUSION

Discussion

The conceptual framework (Figure 3.2) was developed by the researchers, based on the Exploratory Factor Analysis conducted at the onset of the research study. The relationship and correlation between the Independent Variables and the Dependent Variable were revealed through that and this model was developed as an outcome of that.

Figure 3.2: Conceptual Framework



Source: Developed by the researcher

Considering this, three main hypotheses were developed.

H1a – Educational Factors Impact the Employability of BDP

H1b –Skills and Competencies Impact the Employability of BDP.

H1c –Job Market Factors Impact the Employability of BDP.

The outcomes of both the Exploratory Factor Analysis and the Thematic Analysis displayed a significant similarity in spite of the slight differences between responses. Hence the overall findings of the study were justified by two gears, which increased the accuracy and fidelity of the final outcomes.

H1a: Educational Factors Impact the Employability of BDP

DASCA, (2020); the standards body ensures that all its accredited institutions are hiring destinations that are preferred by most organisations. Thus, accreditations of local and foreign bodies have a high impact on the

employability of BDP. Many industry experts commented that there are international accreditation bodies for BDP, which ensures the delivery of quality education to professionals in the field. According to the majority of the respondents, the accreditation bodies of their educational qualifications provide constant guidance and updates about the new trends and developments in the field. This undoubtedly contributes to more updated knowledge of professionals; hence, employers prioritise the standard of accreditations when employing BDP.

Based on the research findings, there are many contemporary crash courses in big data analytics as well; namely, Coursera (2020); EDX, (2020). Industry experts say that these crash courses are effective platforms for learning big data and data analytics, within a shorter time duration, even at a very low cost. They further mention that professionals can be "corporate-ready" after following such standard crash courses.

Even though there are only a few local qualifications on big data analytics, there are many foreign qualifications. SAS in collaboration with Birmingham City University has launched a program called SAS Student Academy, in order to educate potential BDP, with the motive of catering to the growing demand of the professionals (Dhawan & Zanini, 2014). Many local BDP declare that there are not much recognised higher educational platforms for big data analytics in Sri Lanka, which has to become a major concern in order to increase the number of professionals in the job market. Similarly, the interviewers strongly highlighted that many foreign qualifications on big data analytics are much advanced and standardised than local qualifications, which definitely has an impact on the employment of local BDP.

Apart from the traditional academic qualifications, BDP is also offered various platforms to engage in professional education. The experts in the field of big data explicitly mention that platforms such as (AWS, 2020) facilitate this. The Majority of the respondents have stated that they constantly feel the need of a standard professional qualification when working in a corporate setting, in order to update their knowledge and climb up the corporate ladder. However, a concern is brought on the lack of professional qualifications locally, which might be an influential factor contributing to the current big data skill shortage.

H1b: Skills and Competencies Impact the Employment of BDP

Interactive disciplines of Big Data Analysts should embrace soft skills such as critical thinking, creative thinking and communication (Song, 2016). All the respondents of the questionnaire survey commented that soft skills are of

utmost importance to big data employees as well. The industry experts prioritise the communication skills of BDP, since it has a major impact in sharing the findings of big data analytics with the stakeholders. The importance of managing stakeholders, working in teams and being attentive to others are also highlighted as key soft skills required by BDP.

SAS, The Tech partnership, (2014) specified that the employers are explicitly interested in potential BDP with interpersonal, management and business insights. Therefore, managerial skills are another value-added skill for BDP. The majority of the respondents, along with a majority of the interviewers, have agreed that managerial skills are important for employees in the field of big data. The most important factors that managerial skills for BDP include people management, time management, decision making and cognitive skills. However, few experts in the local big data industry have commented that managerial skills do not play much of a big role since big data analysis is a technical field rather than a managerial emphasis.

Royster (2013) stated that rounded up knowledge about the industry that the BDP is employed in will uplift their contribution to the sector. In order to do so, they should possess many competencies polished with traditional and up-to-date proficiencies. Based on the responses of the questionnaire survey, it was concluded that the competency level of local BDP is satisfactory when compared with foreign professionals. However, few experts commented that the possible improvements in competencies are very high. Furthermore, the majority of the experts in the field mentioned that there are competency development programs conducted for BDP by their companies.

H1c: Job Market Factors Impact the Employment of BDP

In Sri Lankan context, JKH (2020) and PickMe, (2016) have specified a minimum of two years of experience in the field for an employee to be recruited as a big data employee. All the industry experts have commented that experience is very important when employing BDP in an organisation. Similarly, big data employees mention that the experience, skills and competencies that they have acquired through past experience has immensely helped them in performing their current job.

Certain employees find their career path based on the prestige of the field. Similarly, BDP also considers the recognition of the profession when engaging in employment. According to Hopkins and Hawking (2018), big data analytics is growing in recognition in the global job market with its rapid evolution and potential strategic competitive inferences. Even though big data analytics is high in recognition in the international job market, it is not so in Sri

Lanka. Industry experts comment that this is mainly because the industry is still in the early stages of emergence. They further explain that only the professionals in the field are aware of the term "Big Data Professionals" and are referred to as "Computer Engineers" in layman terms.

Carillo et al. (2019); Carillo (2017); Intezari & Gressel (2017); Murawski & Bick (2017) stressed the importance of on-the-job training, career guidance and continuous professional development programs to develop analytical and technological skills. Similarly, Wickramasinghe (2017) stressed on "Retrain to retain", to overcome the employee shortfall by training the existing workforce to possess futuristic yet vital data analytic skills.

Many experts mention that even though the existing BDP in Sri Lanka are well-knowledged and talented, there is a scarcity of professionals in order to cater to the growing demand. However, they further mentioned that when compared to the professionals in developed countries, local BDP has so much to develop. When considering the age of professionals, it is very visible that most employees in the field are young and energetic and not very mature in age.

Ferraris et al. (2019) mentioned that efficient implementation of big data analytics should be unquestionably supported by high level software such as NoSQL and Hadoop. Many respondents commented that even though the Sri Lankan big data field is still at maturity levels, their companies adopt new advancements in infrastructure. According to many industry experts, companies consider numerous factors before investing in infrastructure and engage in a lot of research.

Ajah & Nweke (2019) in their study described big data as the Universal Data Fabric and the central core for the entire set of contemporary computing, which creates strong inter-institutional linkages for all corporate employees to work together as a team. Similarly, the majority of big data employees agree that their professional networks help them immensely in performing their current jobs. Whereas industry experts justify this fact by saying that professional networks serve as knowledge bases and information sharing platforms, which help employees gain more exposure and experience.

Conclusion

The research study identified that the employability of BDP is affected by educational factors, skills and competencies and job market factors. The findings were done with reference to the data gathered by big data employees in local logistics companies. The literature review unveiled that big data employees are lacking in the job market at a significant level due to various weaknesses in the aforementioned three factors. Similarly, the industry experts specifically revealed the lack of engagement with the profession locally. Hence, possible actions should be taken to uplift their representation as a prestigious career by mitigating all the shortcomings. The researchers determined that the local higher educational platforms and professional qualifications should be improved and standardised as the initial steps to mitigate the skill shortage of professionals. Similarly, the local employees should be extended with systematic competency development programs in order to continuously nurture their skills. Meanwhile, the profession should be firmly embraced and promoted by local companies with the motive of a "winwin" approach to both the company and BDP. Their remuneration should be improved in line with the amount of value addition they bring to the company. These are possible paths to be ventured in order to bring out the true potential of big data analytics by overcoming the compelling skill shortage of professionals. The study further highlighted the contribution of big data analytics to the battle against the current pandemic situation. Therefore, companies should expand their horizons to grasp this enticing field as a source of growth and competitive advantage.

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