Factors driving business intelligence adoption: an extended technology-organization-environment framework

Radhakrishnan Subramaniam[1,2], Prashobhan Palakeel[3], Manimuthu Arunmozhi[4], Manikandan Sridharan[5], Uthayakumar Marimuthu[6]
[1]DevOps, Automation and AIOps Practice, Singapore Telecommunication Group, Singapore, Singapore
[2]School of Business, Amrita Vishwa Vidyapeetham, Coimbatore, India
[3]Department of Management, School of Business, Amrita Vishwa Vidyapeetham, Coimbatore, India
[4]Department of Operations and Information Management, Aston University, Birmingham, United Kingdom
[5]Department of Information Technology, E.G.S Pillay Engineering College, Nagapattinam, India
[6]Department of Mechanical Engineering, Kalasalingam Academy of Research and Education, Krishnankoil, India

Article Info

Article history:

Received Feb 9, 2024
Revised Feb 22, 2024
Accepted Mar 4, 2024

Keywords:

Adoption framework
BI drivers
Business intelligence
Organizational adoption
Technology adoption
TOE

ABSTRACT

Business intelligence (BI) is a vital component for businesses of all scales, offering actionable insights crucial for timely decision-making. This technology has become integral across diverse enterprises. Recognizing the factors influencing BI adoption is imperative, and this article employs the organization, complexity, knowledge, technology, user perception and experience, economic, environmental, and social (OCKTUEES) framework to identify key aspects. Building upon the TOE framework, it pinpoints significant variables, emphasizing the importance of factors like user perception and experience, technology, social, economical, and environmental. Employing structural equation modelling on primary data yields actionable insights to address BI adoption challenges. Analysis reveals the user perception and experience, technology, social, economic, and environmental as the top factors. However, the organization appears vulnerable, necessitating a mitigation strategy for successful BI adoption. The study predicts insignificant variables requiring mitigation, such as high costs, inadequate resources, organizational size, security and privacy concerns, risk of open-source adoption, and perception of analytics impacting jobs. This research aids those navigating the BI implementation journey.

Corresponding Author:

Radhakrishnan Subramaniam
DevOps, Automation and AIOps Practice, Singapore Telecommunication Group
Singapore: 239739, Singapore
Email: salemradha@gmail.com

1. INTRODUCTION

In the volatile business environment, business requires more insights on their performance against competitors, product performance, customer buy-in for their product and service, industry trends, and so on. Every business from brick and mortar or even modern startup businesses expects business intelligence (BI) or analytics to provide these capabilities for sustainability, competitiveness, and emergence. There are a lot of BI tools in the market that provide such capability as a whole or industry-specific. BI technology provides insights from data to illuminate pathways for improved choices and outcomes [1]. Specifically, BI helps to facilitate access to information and actionable insights in the form of visualizations [2]. The implications of BI extend far and wide, catalyzing business growth [3] and, notably, as a linchpin of competitive advantage [4]. Numerous advantages such as agility, creating innovative products and services [5], and placing competitive advantages in

B2B, B2C, or B2B2C [6]. A tapestry of research has illuminated the positive ripple effects of BI, spanning performance enhancements, knowledge propagation, and a heightened propensity for innovation. Moreover, the synergy of BI with artificial intelligence (AI) emerges as a transformative force, ushering in disruptive changes that underscore competitive advantage [7]. Every stakeholder in the business is required to see BI in their organization to look at performance and insights within the organization and external forces as well. BI is one of the mainstream technologies in business at a micro and macro level. Business needs to understand underlying forces for the successful adoption and implementation of BI within the organization. Technology is just one pillar as there are many pillars needed to support the successful adoption or implementation. There are many technologies adoption frameworks such as technology-organization-environment (TOE), resource-based view (RBV), motivation, opportunity, and ability (MOA), UTAUT, technology assessment model (TAM), and so on in use which focus on specific needs and purposes [8]-[11].

But this specific article [12] tried to combine these frameworks and adopted many factors [factors aka organizations, complexity, knowledge, technology, user perception and usage, economic, environmental, and social (OCKTUEES) framework] to understand the adoption significance of a factor or even independent variables thoroughly. It is important to use such complex models so that significance can be identified to help the stakeholder to mitigate and greater success in adoption or implementation. This article tried to find out the key determinants of BI adoption drivers using the OCKTUEES framework. This article will have subsequent sections relating to the literature background, research model and hypotheses, instrument development, data collection, data analysis, testing hypothesis, results and discussions, implications, conclusions, and recommendations.

2. LITERATURE REVIEW

Numerous benefits arise from the adoption of BI, as highlighted by the literature findings presented in Table 1. It is essential to acknowledge that the enumerated benefits are not exhaustive, and there may be additional advantages that contribute to the overall value of BI implementation. This compilation serves as a glimpse into the positive outcomes associated with BI adoption, emphasizing its multifaceted impact on various aspects of organizational functioning.

The identification and articulation of challenges in previous research have shed light on various obstacles that need to be addressed for the successful adoption of BI in organizations. For a comprehensive overview of these challenges, please refer to Table 2. It is important to note that the list provided is not exhaustive, as there may be additional hurdles that organizations encounter during the implementation of BI solutions. Effectively mitigating these challenges is crucial for realizing the full potential and benefits of BI in enhancing organizational decision-making processes. Our study will employ a robust framework to delve into both significant and insignificant factors and variables that impact BI adoption. This approach aims to provide valuable insights that can guide BI stakeholders in implementing remedial actions and enhancements to improve overall implementation success.

Table 1. Benefits of BI adoption

#	Benefits	Reference
1	Improved decision-making and operational efficiency	[13]
2	Compatibility, relative advantage, and information quality	[14]
3	Provide strong impact on business outcomes	[15]
4	Better insights, consistency, and organizational transformation	[16]
5	Higher level of individual performance	[17]
6	The backbone of organizational decision-making	[18]

Table 2. Challenges in BI adoption

#	Challenges	Reference
1	Evolution of technology and rapid change	[19]
2	Very low success rate in BI implementation. Failed to reap the benefit	[20]
2	Scalability concerns and no agility in the implementation of the platform	[21]
3	Lack of top management support	[22]
4	Security, ethical issues and data privacy concerns	[19]
5	Communication gaps to articulate the usefulness of BI	[19], [20]
6	Interoperability issues since a lot of upstream and downstream connections expected	[23]
7	Data availability and quality of data to present insight	[19]
8	Skill and skill redevelopment expected in IT and non-IT stakeholders	[19]
9	High cost and tangible return	[24]
10	The complexity involved in handling technically	[25], [26]

Numerous adoption frameworks, particularly in the BI domain, have been utilized in previous research. The TOE framework [27] stands out as one of the most prominent and extensively employed models. TOE frameworks have been expanded, incorporating elements from the innovation diffusion theory (IDT). Other noteworthy frameworks include MOA [28], RBV [29], TAM [30], UTAUT [31], and OCKTUEES [12]. Unlike TOE and OCKTUEES, many of these frameworks were tailored for specific purposes. OCKTUEES, however, was developed with a comprehensive approach, encompassing 8 factors and 32 variables to analyze adoption extensively. In this article, we will leverage the OCKTUEES framework to identify both significant factors and variables. This analytical approach aims to provide valuable insights for the BI community.

The objective of this study is to look at significant factors and variables that contribute to the successful adoption of BI in the organization. The following questions will be addressed in this article.

a) What factors influence BI adoption in organizations?
b) What variable(s) causes concern in the successful adoption of BI?

3. METHOD

This article will adhere to Churchill's approach [32] by first selecting a suitable framework. Subsequently, the focus will shift to hypothesis design to address key questions. Following this, an appropriate instrument will be developed for data collection. The collected data will then undergo analysis and testing against the formulated hypotheses. The results will be thoroughly discussed, aiming to articulate the significant factors and variables that contribute to our understanding of BI and serve as valuable contributions to the broader research community. For detailed information, please refer to Figure 1.

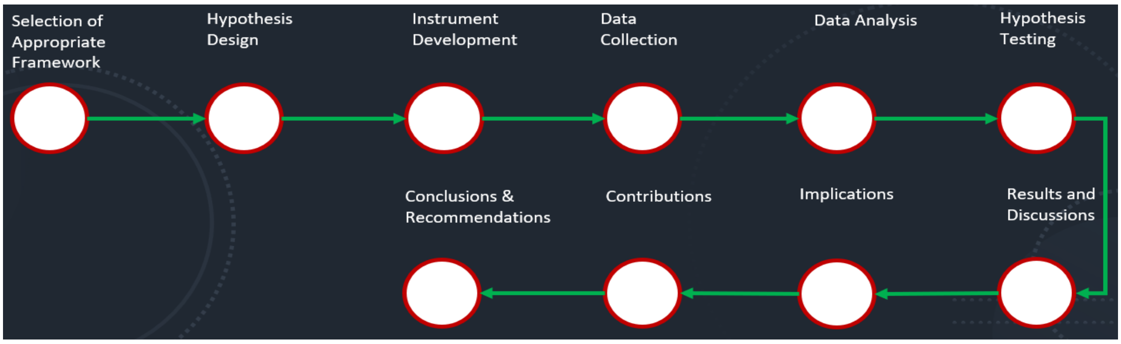

Figure 1. Research method

3.1. Selection of appropriate framework

As mentioned in the section 2 “Literature Review”, this article will use the OCKTUEES framework to test the significance in a complex way rather than just testing with three factors [Technology, Organization, and Environment] in the case of the TOE as this OCKTUEES is an extended framework with 9 factors articulated.

3.2. Hypotheses design

This article is supposed to address the questions to identify the factors that influence the adoption of BI in organizations and at the same time, identify concerned variables which affect BI adoption in organizations. The hypothesis framework as in Figure 2 is already articulated in the previous study as mentioned by Subramian’s article. This article will use those hypothesis frameworks to address question 1. Refer to Figure 3 and the subsequent section for the hypothesis design and details. These hypotheses form the cornerstone of our research journey, encapsulating the multifaceted relationships that underpin the adoption dynamics of BI within organizational landscapes. While analyzing each of the above factors and respective hypotheses as below, variables will be tested for significance as well:

H1: Organization (ORG) factor positively influences BI adoption in the organization
H2: Complexity (COM) factor positively influences BI adoption in the organization
H3: Knowledge (KNO) factor positively influences BI adoption in the organization
H4: Technology (TEH) factor positively influences BI adoption in the organization
H5: User perception and experience (PAE) factor positively influences BI adoption in the organization
H6: Environmental (ENV) factor positively influences BI adoption in the organization
H7: Economic (ECO) factor positively influences BI adoption in the organization
H8: Social (SOC) factor positively influences BI in Organization

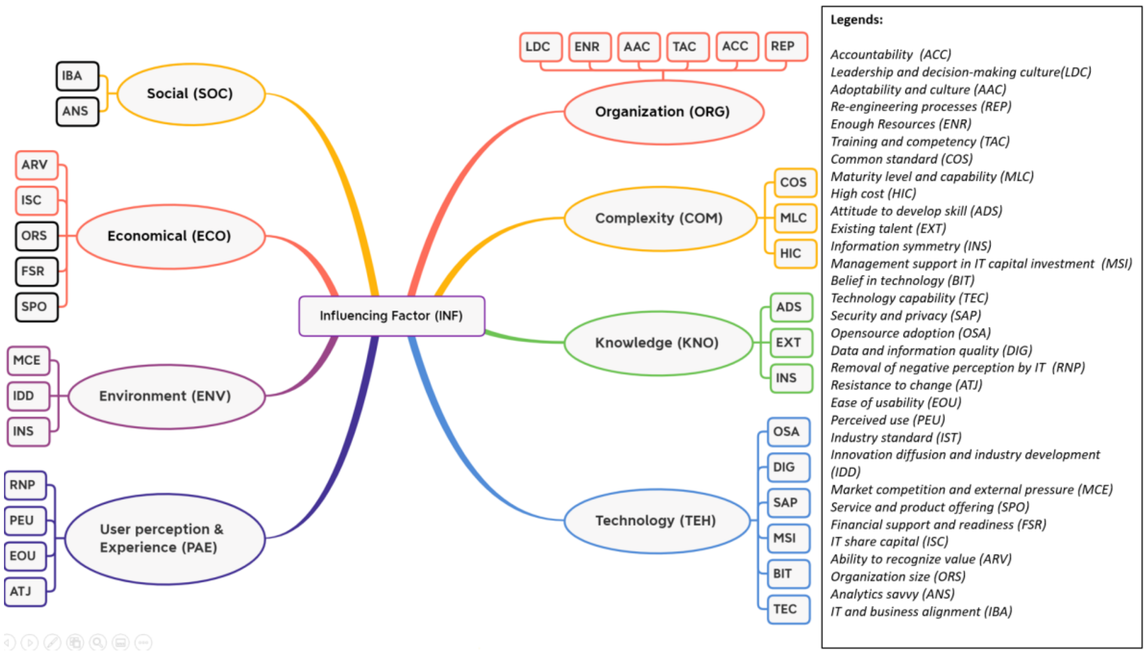

Figure 2. Framework (OCKTUEES) for the identification of significant BI factors and variables [*figure is as-is provided by [12]]

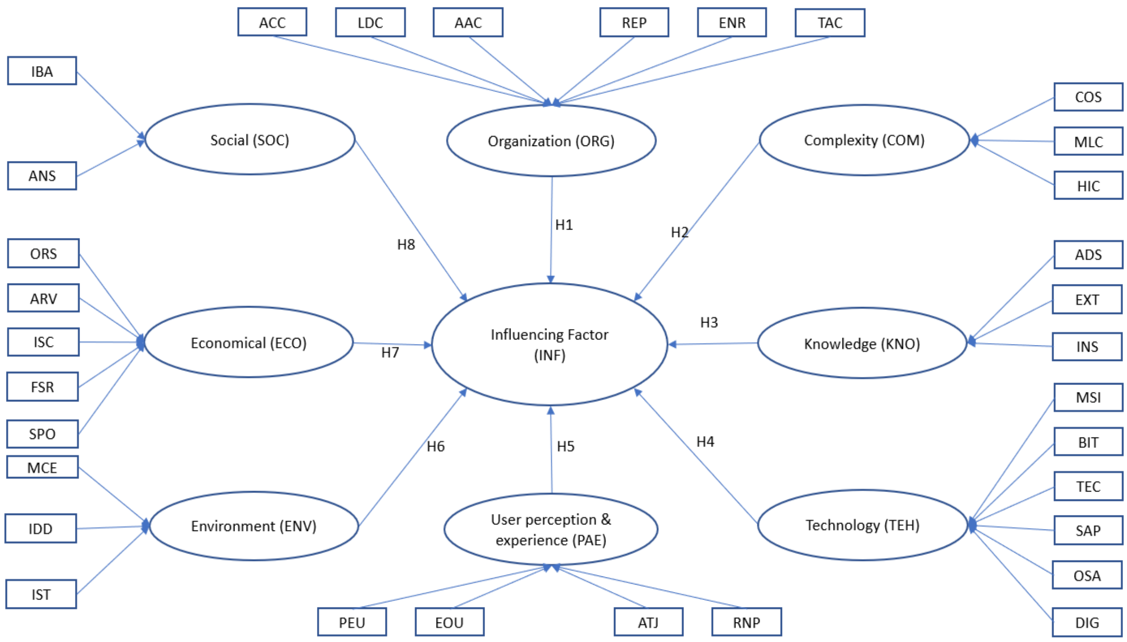

Figure 3. The hypotheses design

3.3. Instrument development and data collection

The survey questionnaires were meticulously structured to capture insights related to the 32 influencing variables (IVs) distributed across the 8 overarching factors as provided in the OCKTUEES framework. In alignment with stringent confidentiality protocols, the collection of respondent information was limited to their name and level of experience, ensuring anonymity. The essence of this approach was to solely associate responses with the respective 32 IV questions. To gauge the nuances of participant perspectives, a 5-point Likert scale was adroitly employed. The scale ranged from "Strongly Agree" with a numerical equivalent of 5, to "Strongly Disagree" represented by 1. Each participant was required to respond to every question in a bid to eliminate potential data gaps and ensure comprehensive insights were garnered. The data collection process was steered by closed-ended questions, adhering to a structured approach to facilitate coherent and insightful responses from the participants.

In this study, respondents were judiciously chosen through a purposive sampling method, meticulously aligning with the research's targeted objectives. The study's focus converged on employees within an enterprise environment, spanning diverse strata of experience levels. To ensure a comprehensive and insightful data collection process, the authors adopted the total design method outlined in the reference [33]. A meticulously crafted survey was disseminated to a pool of 220 recipients. Through a meticulous validation process, duplicate responses were scrupulously eliminated, yielding a total of 203 unique and distinct responses. This cumulative pool of respondents, reflective of an impressive 92.2 percent response rate, underscores the robustness of the empirical dataset [34], thereby substantiating the adequacy of the collected data for subsequent analysis. There are 74 responses from 10 to 20 years of experience, 70 responses from more than + 20 years, and 59 responses from 10 to 20 years of experience.

3.4. Data analysis

To enable meticulous data analysis, we loaded the necessary libraries, including Lavaan 0.6-3 [35], Sem, and Semplot, in the R environment. This approach is in line with best practices in IT and information systems, providing a strong framework for assessing the predictive relationships between the proposed constructs and the dependent variables [36]. The data analysis included 200 bootstrap draws, a statistically recommended estimator for a sample size of 203. To assess construct reliability, Cronbach's alpha was calculated, yielding an overall coefficient of 0.878 and item-wise values exceeding the 0.70 threshold, indicating reliability [37], [38]. For detailed reliability check results, please refer to Table 3. The model fitting process proceeded through 53 iterations, converging at a final model. The results of this detailed process are summarized in Table 4, with Figure 4 providing a graphical representation of the factor loadings. This rigorous data processing and analysis methodology underpins the subsequent findings and insights, ensuring the robustness and credibility of the study's empirical outcomes.

Table 3. Reliability analysis

	Item reliability statistics			
	Mean	Sd	Item-rest correlation	Cronbach's α
ACC	4.05	0.840	0.432	0.874
LDC	4.33	0.798	0.308	0.876
AAC	3.96	0.814	0.365	0.875
REP	3.78	0.956	0.362	0.875
ENR	3.65	1.000	0.167	0.880
TAC	3.99	0.884	0.379	0.875
COS	3.80	0.864	0.424	0.874
MLC	3.99	0.832	0.414	0.874
HIC	2.96	1.153	0.199	0.880
ADS	4.07	0.789	0.403	0.874
EXT	3.74	0.972	0.393	0.875
INS	3.95	0.851	0.494	0.872
MSI	4.13	0.817	0.443	0.874
BIT	4.04	0.940	0.419	0.874
TEC	4.10	0.799	0.528	0.872
SAP	3.66	1.062	0.321	0.877
OSA	3.24	1.060	0.326	0.876
DIG	4.01	0.853	0.370	0.875
PEU	3.78	0.828	0.457	0.873
EOU	4.01	0.823	0.456	0.873
ATJ	3.10	1.117	0.314	0.877
RNP	3.75	0.927	0.450	0.873
MCE	4.00	0.893	0.313	0.876
IDD	3.98	0.820	0.495	0.873
IST	3.51	0.997	0.486	0.872
ORS	3.65	1.063	0.287	0.877
ARV	4.04	0.849	0.380	0.875
ISC	3.69	0.916	0.615	0.870
FSR	4.00	0.847	0.531	0.872
SPO	3.92	0.892	0.510	0.872
IBA	4.10	0.790	0.578	0.871
ANS	3.82	0.927	0.484	0.873

Table 4. Latent variable loading

Latent variables INF =~	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
ORG	1.000				0.621	**0.621**
TEH	1.290	0.322	4.011	0.000	0.958	**0.958**
ENV	1.008	0.350	2.878	0.004	0.906	**0.906**
COM	1.118	0.283	3.953	0.000	0.755	**0.755**
KNO	1.072	0.296	3.615	0.000	0.845	**0.845**
PAE	1.3O4	0.375	3.473	0.001	0.965	**0.965**
ECO	0.981	0.365	2.688	0.007	0.940	**0.940**
SOC	1.617	0.382	4.233	0.000	0.951	**0.951**

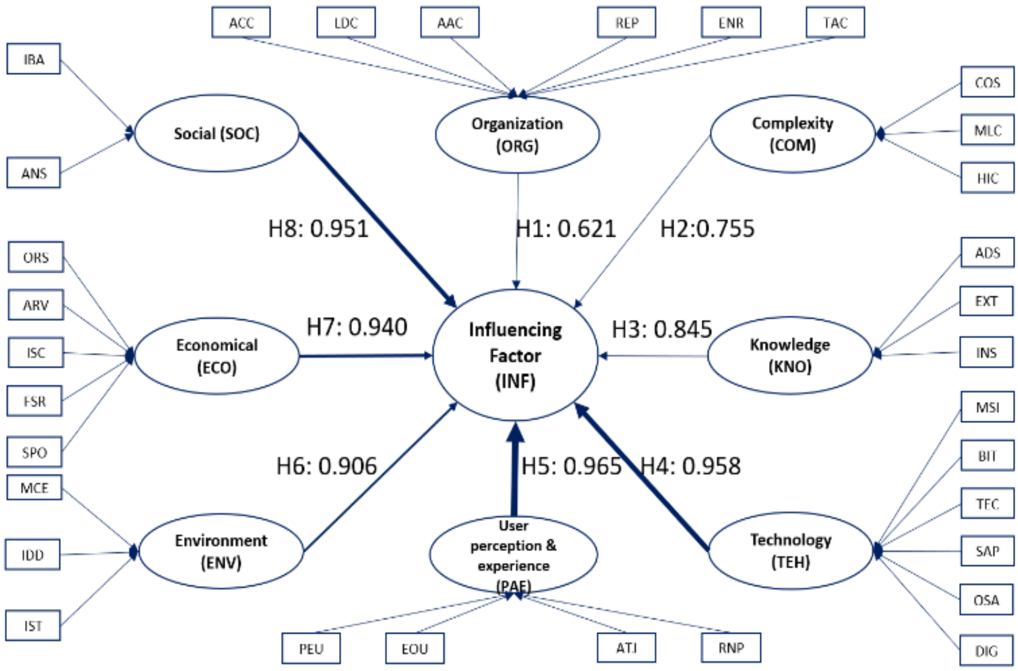

Figure 4. Factor loading

An all-encompassing evaluation of the goodness-to-fit underscores a highly favorable alignment between the proposed model and the empirical data. The summary statistics reveal a robust fitting, attested by the following indices.

- Goodness of fit index (GFI): impressive at 0.932 (GFI ≥0.95) [39], [40]
- Adjusted goodness of fit index (AGFI): strong at 0.922 (AGFI >0.90) [39], [40]
- Tucker-lewis index (TLI): exceptional at 0.993 (TLI ≥0.95) [39], [40]
- Comparative fit index (CFI): excellent at 0.994 (CFI ≥0.90) [39], [40], [41]
- Root mean square error of approximation (RMSEA): minimal at 0.015 (RMSEA <0.08) [39], [40]
- Standardized root means square residual (SRMR): favorable at 0.076 (SRMR <0.08) [39], [40]

3.5. Testing the hypothesis

Upon a comprehensive examination of factor significance, coupled with the outcomes as illustrated in Table 5, a clear pattern emerges. This discerning analysis hinges exclusively on the upper echelon of factor loadings, providing a succinct yet insightful snapshot of the key factors that wield substantial significance in shaping the landscape of BI adoption within organizational realms. Among the array of factors under scrutiny, the top five that bear the most notable influence are:

- PAE (use perception and experience)
- TEH (technology)
- SOC (social)
- ECO(economical)
- ENV (environmental)

Table 5. Overall factor loading

Latent variables: [*this output is extracted from SEM]						
	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
ORG =~						
ACC	1.000				0.510	0.607
LDC	0.741	0.201	3.680	0.000	0.378	0.473
AAC	0.880	0.216	4.076	0.000	0.449	0.552
REP	0.961	0.242	3.967	0.000	0.490	0.513
ENR	0.532	0.228	2.332	0.020	0.271	0.271
TAC	0.901	0.246	3.665	0.000	0.459	0.519
TEH =~						
MSI	1.000				0.427	0.523
BIT	1.063	0.180	5.899	0.000	0.454	0.483
TEC	1.110	0.153	7.256	0.000	0.473	0.593
SAP	0.798	0.267	2.991	0.003	0.340	0.321
OSA	0.815	0.231	3.523	0.000	0.348	0.328
DIG	0.805	0.191	4.215	0.000	0.344	0.403
ENV =~						
MCE	1.000				0.353	0.395
IDD	1.390	0.511	2.719	0.007	0.490	0.597
IST	1.533	0.652	2.350	0.019	0.540	0.542
COM =~						
COS	1.000				0.469	0.543
MLC	0.970	0.221	4.396	0.000	0.455	0.547
HIC	0.606	0.263	2.305	0.021	0.284	0.247
KNO =~						
ADS	1.000				0.402	0.509
EXT	1.171	0.264	4.430	0.000	0.471	0.484
INS	1.300	0.223	5.822	0.000	0.523	0.614
PAE =~						
PEU	1.000				0.428	0.517
EOU	0.986	0.201	4.915	0.000	0.423	0.513
ATJ	0.860	0.241	3.565	0.000	0.369	0.330
RNP	1.100	0.261	4.221	0.000	0.471	0.508
ECO =~						
ORS	1.000				0.331	0.311
ARV	1.164	0.798	1.459	0.145	0.385	0.454
ISC	1.896	1.042	1.820	0.069	0.627	0.685
FSR	1.604	0.876	1.832	0.067	0.531	0.626
SPO	1.596	0.917	1.740	0.082	0.528	0.592
SOC =~						
IBA	1.000				0.539	0.682
ANS	0.930	0.121	7.712	0.000	0.501	0.541
INF =~						
ORG	1.000				0.621	0.621
TEH	1.290	0.322	4.011	0.000	0.958	0.958
ENV	1.008	0.350	2.878	0.004	0.906	0.906
COM	1.118	0.283	3.953	0.000	0.755	0.755
KNO	1.072	0.296	3.615	0.000	0.845	0.845
PAE	1.304	0.375	3.473	0.001	0.965	0.965
ECO	0.981	0.365	2.688	0.007	0.940	0.940
SOC	1.617	0.382	4.233	0.000	0.951	0.951

Upon review, ORG is not among the top five significant factors, as its loading (0.621) is below the desired threshold of 0.70. Previous research [42]-[45] has explored the relationship between technology, organization, and environment to identify other influencing factors. Therefore, in this context, the impact of the organization factor on BI adoption is not a primary focus. COM is a less influential factor, with a loading of 0.755 (>0.70, meeting significance) [46]. In the current BI landscape, characterized by maturity, complexity is no longer a significant challenge. However, the IV high cost (HIC) fails to exhibit significance, with a poor loading of 0.25<0.40. Although Complexity remains significant at 0.755, it does not rank among the top five influential factors. KNO emerges as the third least influential factor, with a loading of 0.845 (> 0.70, indicating significance). Three IVs – ADS, EXT, and INS – are associated with the KNO construct. The prevalence of information symmetry, facilitated by technology's integration across business and consumer realms, might explain this trend. While knowledge is a positive driver for BI adoption, it does not rank among the top five significant factors. Technology is the second-most influential factor, with a loading of 0.958 (>0.70, demonstrating significance). It plays a pivotal role in reducing volatility in BI adoption. IVs like MSI, BIT, TEC, and DIG contribute collectively to solidify Technology's significance. Although individual loadings of security and privacy (SAP) and open-source adoption (OSA) are poor at 0.32 and 0.328 respectively, Technology remains crucial due to BI's integration within the technological landscape and its role in product differentiation and competitive edge.

PAE stands as the most influential factor, with a loading of 0.965 (>0.70, signifying significance). Comprising IVs PEU, EOU, ATJ, and RNP, PAE's supremacy underscores the pivotal role of user experience and perception, profoundly influencing marketplace dynamics. Despite the analytics takeaway job (ATJ) having a poor loading of 0.33<0.40, PAE remains the most potent driving force for BI adoption. ENV assumes the fifth position in influence, with a loading of 0.906 (>0.70, denoting significance). IVs MCE, IDD, and IST contribute to this construct. This study highlights the critical role of environmental factors, encompassing market competition and external pressures, in propelling BI adoption within organizations. ECO ranks as the fourth influential factor, with a loading of 0.940 (>0.70, indicating significance). Comprising IVs ORS, ARV, ISC, FSR, and SPO, ECO's significance is underscored by the essential roles of ORS and ARV in BI adoption [8], [47], [48], despite ORS loading 0.31<0.40. All other IVs (ARV, ISC, FSR, and SPO) loaded significantly, emphasizing the influence of Economic contexts on BI adoption. SOC emerges as the third most significant factor, with a loading of 0.951 (>0.70, signifying significance). Encompassing IBA and ANS as its IVs, SOC's prominence resonates with findings from prior literature highlighting conflicts between IT and business custodians [49]. Given the significance of IT-business alignment, especially in the digital transformation era, the social factor plays a pivotal role in reducing uncertainties and fostering BI adoption. To address question 2, the insignificant variables <0.40 and their loadings are listed below in Table 6.

Table 6. Loading of insignificant variables

Factor	Variable	Loading
Organization (ORG)	Enough resource (ENR)	0.271
Technology (TEH)	Security and privacy (SAP)	0.321
Technology (TEH)	Opensource adoption (OSA)	0.328
Complexity (COM)	High cost (HIG)	0.247
User perception and experience (PAE)	Analytics takeaway job (ATJ)	0.330
Economical (ECO)	Organization size (ORS)	0.311

4. RESULTS AND DISCUSSIONS

Table 4 summarizes the significance of 8 factors from the data analysis in chronological order. The top 5 significant factors are:

- PAE (use perception and experience): highly significant at 0.965
- TEH (technology): markedly substantial at 0.958
- SOC (social): notably significant at 0.951
- ECO (economical): demonstrates significance at 0.940
- ENV (environmental): evidences significance at 0.906

The other three factors are loaded with the following significant rate.

- KNO (knowledge): reflects significance at 0.845
- COM (complexity): presents significance at 0.755
- ORG (organization): exhibits significance at 0.621

Standardized loading is significant for all factors except ORG. PAE is the most influential, with loadings ranging from 0.330 to 0.517. TEH follows with loadings between 0.321 and 0.593. SOC stands as the third significant factor, with loadings from 0.541 to 0.682. ECO ranks fourth, with variable loadings between 0.311 and 0.685, while ENV holds the fifth spot with loadings from 0.395 to 0.597. Previous studies explored BI in diverse contexts, like agility in cloud computing [50] and user experience in BI and analytics [36]. However, these studies highlighted the omission of factors like trialability and user experience in utility theory, emphasizing the critical roles of PAE, TEH, and SOC in BI adoption. Table 5 presents variables of concern in BI adoptions. Under the organization factor, "enough resources (ENR)" is identified as insignificant, requiring a mitigation plan. Within the technology factor, "security and privacy (SAP)" and "opensource adoption (OSA)" are flagged as major concerns, requiring targeted strategies. High costs in the complexity factor demand a focus on acquiring technology with optimal costs and higher ROI. In the realm of user perception and experience, the concern of "analytics taking away jobs" requires a comprehensive strategy. Additionally, organization size, identified under the economic factor, influences successful implementation, requiring clarification given the diverse range of BI tools available.

5. CONTRIBUTIONS

The author is motivated to extend part one of a previous study [12] by developing the OCKTUEES framework further in part two for deeper insights. The insights from this paper benefit organizations embarking on the BI adoption journey by identifying the most significant factors for successful adoption. The OCKTUEES model highlights user perception and experience (PAE) as the most significant, which is not part of the factors in the TOE framework. Past literature has examined the interplay between technology, organization, and environment to uncover alternative influencing factors [42]-[45]. The third and fourth factors, SOC and ECO are also significant but not part of the TOE framework. These three factors, along with technology and environment, play a major role in the current competitive world. The organization factor is no longer a top significant factor, as organizational maturity facilitates a seamless transition by embedding technology in the business mainstream. This article further explores the most significant driver from the variable perspective. Ease of usability (EOU) and removal of negative IT perception (RNP) are two variables in PAE that can drive adoption faster. Stakeholders need to emphasize these variables for greater success. Similarly, IT share capital (ISC), financial support, and readiness (FSR), and service and product offering (SPO) are the most significant variables under economic. BI stakeholders need to focus on driving these variables for faster adoption. IT and business alignment (IBA) and analytics savvy (ANS) under SOC are highly rated, driving adoption faster.

6. CONCLUSION

The OCKTUEES framework sheds light on adoption behaviors, identifying perception and user experience, technology, social, economic, and environmental as key drivers of BI adoption. Examining these factors in detail reveals specific IVs integral to their significance. Notable concerns include ORG [enough resource], TEH [security and privacy and opensource adoption], COM [high cost], PAE [analytics takeaway job], and ECO [organization size]. This perspective can assist the BI community and stakeholders in proactive mitigation and strategy planning for successful implementation and adoption.

REFERENCES

[1] R. Agarwal and V. Dhar, "Big data, data science, and analytics: The opportunity and challenge for IS research," *Information Systems Research*, vol. 25, no. 3, pp. 443–448, Sep. 2014, doi: 10.1287/isre.2014.0546.
[2] A. Gangotra and R. Shankar, "Strategies in managing risks in the adoption of business analytics practices: A case study of a telecom service provider," *Journal of Enterprise Information Management*, vol. 29, no. 3, pp. 374–399, Apr. 2016, doi: 10.1108/JEIM-10-2014-0096.
[3] C. Kuntonbutr and M. Kulken, "The effect of business intelligence on business unit strategies, international operations and business growth," *Journal of Economic and Management Perspectives*, vol. 11, no. 3, pp. 1800–1807, 2017.
[4] T. Guarda, F. M. Pinto, J. P. Cordova, F. Mato, G. N. Quina, and M. F. Augusto, "Pervasive business intelligence as a competitive advantage," in *Iberian Conference on Information Systems and Technologies, CISTI*, Jun. 2016, vol. 2016-July, doi: 10.1109/CISTI.2016.7521569.
[5] Y. Park, O. A. El Sawy, and P. C. Fiss, "The role of business intelligence and communication technologies in organizational agility: A configurational approach," *Journal of the Association for Information Systems*, vol. 18, no. 9, pp. 648–686, Oct. 2017, doi: 10.17705/1jais.00001.
[6] R. Eidizadeh, R. Salehzadeh, and A. C. Esfahani, "Analysing the role of business intelligence, knowledge sharing and organisational innovation on gaining competitive advantage," *Journal of Workplace Learning*, vol. 29, no. 4, pp. 250–267, May 2017, doi: 10.1108/JWL-07-2016-0070.
[7] P. Vardarlier and C. Zafer, "Use of artificial intelligence as business strategy in recruitment process and social perspective," in *Contributions to Management Science*, Springer International Publishing, 2020, pp. 355–373.
[8] K. P. Agrawal, "Investigating the determinants of Big Data Analytics (BDA) adoption in asian emerging economies," *2015 Americas Conference on Information Systems, AMCIS 2015*, vol. 2015, no. 1, p. 11290, Jan. 2015, doi: 10.5465/ambpp.2015.11290abstract.
[9] V. Bhatiasevi and M. Naglis, "Elucidating the determinants of business intelligence adoption and organizational performance," *Information Development*, vol. 36, no. 1, pp. 78–96, Dec. 2020, doi: 10.1177/0266666918811394.
[10] L. Sun *et al.*, "HpQTL: A geometric morphometric platform to compute the genetic architecture of heterophylly," *Briefings in Bioinformatics*, vol. 19, no. 4, pp. 603–612, Feb. 2018, doi: 10.1093/bib/bbx011.
[11] P. Wang, S. W. Palocsay, J. Shi, and M. M. White, "Examining undergraduate students' attitudes toward business statistics in the United States and China," *Decision Sciences Journal of Innovative Education*, vol. 16, no. 3, pp. 197–216, Jul. 2018, doi: 10.1111/dsji.12159.
[12] S. Radhakrishnan, "(PDF) Revolutionizing business intelligence: Pioneering an enhanced adoption framework through the technology-organization- environment paradigm," *Preprint*, p. 8, Dec. 2024, doi: 10.21203/rs.3.rs-3304963/v1.
[13] H. Hmoud, A. S. Al-Adwan, O. Horani, H. Yaseen, and J. Z. Al Zoubi, "Factors influencing business intelligence adoption by higher education institutions," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 9, no. 3, p. 100111, Sep. 2023, doi: 10.1016/j.joitmc.2023.100111.
[14] Z. Jaradat, A. Al-Dmour, H. Alshurafat, H. Al-Hazaima, and M. O. Al Shbail, "Factors influencing business intelligence adoption: evidence from Jordan," *Journal of Decision Systems*, pp. 1–21, Jun. 2022, doi: 10.1080/12460125.2022.2094531.
[15] S. Rouhani, A. Ashrafi, A. Zare Ravasan, and S. Afshari, "The impact model of business intelligence on decision support and organizational benefits," *Journal of Enterprise Information Management*, vol. 29, no. 1, pp. 19–50, Feb. 2016, doi: 10.1108/JEIM-12-2014-0126.
[16] T. Ramakrishnan, M. C. Jones, and A. Sidorova, "Factors influencing business intelligence (BI) data collection strategies: An empirical investigation," *Decision Support Systems*, vol. 52, no. 2, pp. 486–496, Jan. 2012, doi: 10.1016/j.dss.2011.10.009.
[17] C. K. Hou, "Examining the effect of user satisfaction on system usage and individual performance with business intelligence systems: An empirical study of Taiwan's electronics industry," *International Journal of Information Management*, vol. 32, no. 6, pp. 560–573, Dec. 2012, doi: 10.1016/j.ijinfomgt.2012.03.001.

[18] A. M. Stjepić, L. Sušac, and D. S. Vugec, "Technology, organizational and environmental determinants of business intelligence systems adoption in croatian SME: a case study of medium-sized enterprise," *International Journal of Economics and Management Engineering*, vol. 13, no. 5, pp. 737–742, 2019.
[19] C. Lennerholt, J. Van Laere, and E. Söderström, "User-related challenges of self-service business intelligence," *Information Systems Management*, vol. 38, no. 4, pp. 309–323, Sep. 2021, doi: 10.1080/10580530.2020.1814458.
[20] N. U. Ain, G. Vaia, W. H. DeLone, and M. Waheed, "Two decades of research on business intelligence system adoption, utilization and success – A systematic literature review," *Decision Support Systems*, vol. 125, p. 113113, Oct. 2019, doi: 10.1016/j.dss.2019.113113.
[21] H. Wulandari and T. Raharjo, "Systematic literature and expert review of agile methodology usage in business intelligence projects," *Journal of Information Systems Engineering and Business Intelligence*, vol. 9, no. 2, pp. 214–227, Nov. 2023, doi: 10.20473/jisebi.9.2.214-227.
[22] H. C. Wang, "Distinguishing the adoption of business intelligence systems from their implementation: The role of managers personality profiles," *Behaviour and Information Technology*, vol. 33, no. 10, pp. 1082–1092, Feb. 2014, doi: 10.1080/0144929X.2013.869260.
[23] B. Oumkaltoum, E. B. Mohamed Mahmoud, and E. B. Omar, "Toward a business intelligence model for challenges of interoperability in egov system: Transparency, scalability and genericity," Apr. 2019, doi: 10.1109/WITS.2019.8723756.
[24] T. H. Davenport and J. G. Harris, "Leading the way towards better business insights," *Strategic HR Review*, vol. 9, no. 4, pp. 28–33, Jun. 2010, doi: 10.1108/14754391011050388.
[25] T. H. Davenport, "From analytics to artificial intelligence," *Journal of Business Analytics*, vol. 1, no. 2, pp. 73–80, Jul. 2018, doi: 10.1080/2573234X.2018.1543535.
[26] P. Lautenbach, K. Johnston, and T. Adeniran-Ogundipe, "Factors influencing business intelligence and analytics usage extent in South African organisations," *South African Journal of Business Management*, vol. 48, no. 3, pp. 23–33, Sep. 2017, doi: 10.4102/sajbm.v48i3.33.
[27] K. Božič and V. Dimovski, "Business intelligence and analytics for value creation: The role of absorptive capacity," *International Journal of Information Management*, vol. 46, pp. 93–103, Jun. 2019, doi: 10.1016/j.ijinfomgt.2018.11.020.
[28] L. Wang, M. Yang, Z. H. Pathan, S. Salam, K. Shahzad, and J. Zeng, "Analysis of influencing factors of big data adoption in Chinese enterprises using DANP technique," *Sustainability (Switzerland)*, vol. 10, no. 11, p. 3956, Oct. 2018, doi: 10.3390/su10113956.
[29] V. Moreno, F. E. L. Vieira da Silva, R. Ferreira, and F. Filardi, "Complementarity as a driver of value in business intelligence and analytics adoption processes," *Revista Ibero-Americana de Estratégia*, vol. 18, no. 1, pp. 57–70, 2019, doi: 10.5585/ijsm.v18i1.2678.
[30] I. A. A. Alsibhawi, J. B. Yahaya, and H. B. Mohamed, "Business intelligence adoption for small and medium enterprises: conceptual framework," *Applied Sciences (Switzerland)*, vol. 13, no. 7, p. 4121, Mar. 2023, doi: 10.3390/app13074121.
[31] V. Venkatesh, J. Y. L. Thong, and X. Xu, "Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology," *MIS Quarterly: Management Information Systems*, vol. 36, no. 1, pp. 157–178, 2012, doi: 10.2307/41410412.
[32] G. A. Churchill, "A paradigm for developing better measures of marketing constructs," *Journal of Marketing Research*, vol. 16, no. 1, pp. 64–73, Feb. 1979, doi: 10.1177/002224377901600110.
[33] V. R. Sreedharan, G. V. Gopikumar, S. Nair, A. Chakraborty, and J. Antony, "Assessment of critical failure factors (CFFs) of Lean Six Sigma in real life scenario: Evidence from manufacturing and service industries," *Benchmarking*, vol. 25, no. 8, pp. 3320–3336, Nov. 2018, doi: 10.1108/BIJ-10-2017-0281.
[34] R. Dubey, A. Gunasekaran, S. J. Childe, C. Blome, and T. Papadopoulos, "Big data and predictive analytics and manufacturing performance: integrating institutional theory, resource-based view and big data culture," *British Journal of Management*, vol. 30, no. 2, pp. 341–361, Apr. 2019, doi: 10.1111/1467-8551.12355.
[35] Y. Rosseel, *Lavaan: an R package for structural equation modeling and more version 0.5-12 (BETA).; 2012.* 2020.
[36] J. Jaklič, T. Grublješič, and A. Popovič, "The role of compatibility in predicting business intelligence and analytics use intentions," *International Journal of Information Management*, vol. 43, pp. 305–318, Dec. 2018, doi: 10.1016/j.ijinfomgt.2018.08.017.
[37] D. Mishra, Z. Luo, B. Hazen, E. Hassini, and C. Foropon, "Organizational capabilities that enable big data and predictive analytics diffusion and organizational performance: A resource-based perspective," *Management Decision*, vol. 57, no. 8, pp. 1734–1755, Sep. 2019, doi: 10.1108/MD-03-2018-0324.
[38] Revelle W., "psych: Procedures for psychological, psychometric, and personality research (R package version 1.5. 8)," 2017. https//CRAN. R-project. org/package= psych.
[39] G. A. Tetteh, "Assessing indicators of motivation for learning in a TQM class," *TQM Journal*, vol. 27, no. 4, pp. 412–434, Jun. 2015, doi: 10.1108/TQM-03-2015-0037.
[40] R. B. Kline, *Principles and practice of structural equation modeling*. Google Book, 2010.
[41] S. A. Rose, B. Markman, and S. Sawilowsky, "Limitations in the systematic analysis of structural equation model fit indices," *Journal of Modern Applied Statistical Methods*, vol. 16, no. 1, p. 5, 2017.
[42] D. Nam, J. Lee, and H. Lee, "Business analytics adoption process: An innovation diffusion perspective," *International Journal of Information Management*, vol. 49, pp. 411–423, Dec. 2019, doi: 10.1016/j.ijinfomgt.2019.07.017.
[43] R. D. Raut, S. K. Mangla, V. S. Narwane, B. B. Gardas, P. Priyadarshinee, and B. E. Narkhede, "Linking big data analytics and operational sustainability practices for sustainable business management," *Journal of Cleaner Production*, vol. 224, pp. 10–24, Jul. 2019, doi: 10.1016/j.jclepro.2019.03.181.
[44] S. Wang, W. Yeoh, G. Richards, S. F. Wong, and Y. Chang, "Harnessing business analytics value through organizational absorptive capacity," *Information and Management*, vol. 56, no. 7, p. 103152, Nov. 2019, doi: 10.1016/j.im.2019.02.007.
[45] H. Yu, Y. Shi, Y. Yu, J. Liu, F. Yang, and J. Wu, "Business analytics: online promotion with gift rewards," *Annals of Operations Research*, vol. 291, no. 1–2, pp. 1061–1076, Mar. 2020, doi: 10.1007/s10479-019-03193-3.
[46] R. P. Bagozzi and Y. Yi, "Specification, evaluation, and interpretation of structural equation models," *Journal of the Academy of Marketing Science*, vol. 40, no. 1, pp. 8–34, Aug. 2012, doi: 10.1007/s11747-011-0278-x.
[47] S. Malladi, "Adoption of business intelligence and analytics in organizations–an empirical study of antecedents," *AMCIS*, 2013, [Online]. Available: https://aisel.aisnet.org/amcis2013/BusinessIntelligence/GeneralPresentations/3.
[48] P. S. Lai *et al.*, "Imaging phenotype of occupational endotoxin-related lung function decline," *Environmental Health Perspectives*, vol. 124, no. 9, pp. 1436–1442, Sep. 2016, doi: 10.1289/EHP195.
[49] P. Mikalef, R. van de Wetering, and J. Krogstie, "Big data enabled organizational transformation: The effect of inertia in adoption and diffusion," in *Lecture Notes in Business Information Processing*, vol. 320, Springer International Publishing, 2018, pp. 135–147.
[50] D. Larson and V. Chang, "A review and future direction of agile, business intelligence, analytics and data science," *International Journal of Information Management*, vol. 36, no. 5, pp. 700–710, Oct. 2016, doi: 10.1016/j.ijinfomgt.2016.04.013.

BIOGRAPHIES OF AUTHORS

Radhakrishnan Subramaniam Ph.D. Scholar, School of Business, Amrita Vishwa Vidyapeetham, Coimbatore, India. Right now, managing practice [Director] for DevOps, Automation, and AIOps in Singapore Telecommunication Group, Singapore. More than 33 years of IT experience [7 years domestically and 26 years international]. Involved in digital transformation and digital disruption by transforming many government agencies to mitigate digital disruption and aligned with the AGILITY framework to stay relevant. Also, managing technology governance, new IT services development, and establishing enterprise architecture and technology roadmap. Managed overall IT operations for the MNCs which spread across 15+ countries globally. A very strong disruptor and capability enabler for the recent trends such as Infrastructure as Code [IaC], Configuration as Code [CaC], Operation as Code [OaC], and Artificial intelligence for IT Operations [AIOps]. For more info, refer to LinkedIn profile here (https://www.linkedin.com/in/subramaniamradha/). He can be contacted at email: salemradha@gmail.com.

Dr. Prashobhan Palakkeel is an Assistant Professor at the Amrita School of Business, Coimbatore Campus. He also serves as the chairman of the Artificial Intelligence and Business Analytics area. He completed his doctoral research at the Institute for Social and Economic Change (ISEC), Bangalore. He is a passionate researcher and teacher with over 20 years of experience. He has successfully guided a few Ph.D. students at the Amrita School of Business. He has taught and trained people in business analytics, research methods, quantitative methods, and statistical programming using R and Python. As a researcher, he focuses on econometric and machine-learning applications in the economics and finance area and has published articles in national and international journals. For more info, refer to LinkedIn profile here (https://www.linkedin.com/in/prashobhan-palakkeel-77700a4/). He can be contacted at email: palakkeel@gmail.com.

Dr. Manimuthu Arunmozhi is currently an Assistant Professor (Lecturer) in Cybersecurity and Business Analytics at Aston Business School. Before joining Aston University, he worked in the field of Autonomous Vehicle Security at Nanyang Technological University (NTU), Singapore. His work at NTU is not limited to autonomous vehicle simulation, threat analysis, vulnerability assessment, and network security. He has a strong background in automation, autonomous operations, digital control, AI, and cybersecurity. He holds a patent for his invention "Intelligent Metering and Controlling System for Transformers". His research areas include ICT, sustainable operations and information management, threat analysis, and risk assessment, Blockchain, Automation control, cybersecurity, and autonomous vehicles threat and vulnerability assessment. Also, he is an adjunct professor at the University of La Sabana Colombia and handled classes for both undergraduate and postgraduate students from various domains. He also acted as an external expert and keynote speaker on various operations and information system-related topics in various universities including the University of Bradford (UK), NITIE (India), IIM Sambalpur (India), etc. For more info, refer to LinkedIn profile here (https://www.linkedin.com/in/drmanimuthu/). He can be contacted at email: maniasaldhinesh@gmail.com.

Manikandan Sridharan Associate and Head/ Chairman (Board of Studies) of Information Technology in E.G.S Pillay Engineering College (Autonomous), Nagapattinam. I completed Ph.D. from Anna University in the year of 2020, an M.E. (CSE) with University Rank Holder and Distinction from Annamalai University in the year of 2012, and a B.Tech. (IT) with Distinction from E.G.S. Pillay Engineering College in Nagapattinam in the year of 2010. Also, a member of IEEE, ACM, MIE, CSTA, IAENG, CSI, and ISTE. Currently, I am doing research in Artificial Intelligence, Deep Learning, and Data Analytics. Recognized Supervisor (Ref. No.:4040100) from Anna University. For more info, refer to LinkedIn profile here (https://www.linkedin.com/in/manikandan-sridharan-6b303778/). He can be contacted at email: profmaninvp@gmail.com.

Uthayakumar Marimuthu Professor, Department of Mechanical Engineering, Kalasalingam Academy of Research and Education, Tamil Nadu India. So far more than 225 papers and one of the top scientists in India. Around 20 years of teaching experience and a wide topic of publication so far. For more info, refer to LinkedIn profile here (ttps://www.linkedin.com/in/uthayakumar-marimuthu-bb7783b1/). He can be contacted at email: uthayakumar@gmail.com.