A Study on the Application Measurement of Agile Processes, Enterprise Agility and the Emerging Technologies

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This Thesis is dedicated to God for seeing me through this process and My Family members, both nuclear and extended, you have always been my backbone. I specially want to dedicate this to my brother "*Oluwatobi B. Elemo*", God will bring you back to us.

Abstract

Technological disruptions have created dynamic situations and organisations seek to remain agile, whilst enhancing its strategic and operational capabilities for competitive advantages. This has become inevitable, as the utilisation of Enterprise Agility (EA) as a mediating effect and Big Data Analytics (BDA) for Customer Satisfaction (Cs) due to performance purposes, could help speed up data-driven processes and enhance internal and external organisational capabilities. With the aim of exploiting BDA and Intelligent Automation (IA) as emerging technologies, to improve agile processes and effect a stable technological platform for change management practices, this research thesis further investigates measures to advance service organisational processes for performance optimisation. This process builds upon an Intelligent Automated (IA) platform as it implements vital security awareness based on policies for cybersecurity measures.

The thesis reviews systematically, literature from the SCOPUS database library by investigating theoretical lenses, mediators and or moderators, key arguments, and findings. It further builds upon these existing views and hypothetical models to derive hypothesis for determining strategic operability procedures for agile process development and competitive advantages.

Using a quantitative approach based on positivism and exploring a neutral service organisation as a case study, this research further analyses the interrelationship amongst variable capabilities of BDA, EA, OP and Cs using Structural Equation Modelling (SEM) approach. Following the results obtained with respect to its significant level, a framework for IA systems in service organisations is developed. This is then implemented into an analytical dashboard application for measuring agility level and implementing service management practices.

Outcomes of this research contributes uniquely to literature and for practices as it provides the awaited need for organisations to assess its agility level, based on change management principles for competitive advantages. It also integrates Security Orchestration, Automation Response (SOAR) framework policies in service organisations to help to detect and trigger actionable security operations due to cybercrimes, by automating remediated actions. Therefore, enabling agile practices.

Acknowledgement

I would like to use this opportunity to thank God Almighty for seeing me through this research. It has been filled with the good, bad, and ugly, yet, in God's faith, I still shine through.

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Nomenclature

Acronyms – List of Abbreviations

AGFI	Adjusted Goodness of Fit Index
AI	Artificial Intelligence
BPM	Business Process Management
Cs	Customer Satisfaction
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
BDA	Big Data Analytics
EA	Enterprise Agility
ET	Emerging Technology
GFI	Goodness of Fit Index
IA	Intelligent Automation
IAP	Incident Access Process
ISI	Information System Infrastructures
ML	Machine Learning
MTTD	Mean-Time-To-Detect
MTTR	Mean-Time-To-Respond
MVN	Multivariate Normality Assumption
OP	Organisational Performance
PF	Firm Performance
ORDS	Oracle Rest Data Service

RPA	Robotic Process Automation
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modelling
SOAR	Security Orchestration, Automated Response
SRMR	Standardized Root Mean Square Residual

Research Publications

1. O. C. Williams and F. Olajide, “Intelligent Automation and Cybersecurity Procedures for Business Processes”, 2022 ICITST in cooperation with WorldCIS, WCST, WCICSS-2022.
2. O. C. Williams and F. Olajide, "Towards the Design of an Intelligent Automation Framework for Business Processes," *2022 5th International Conference on Information and Computer Technologies (ICICT)*, New York, NY, USA, 2022, pp. 13-17, doi: 10.1109/ICICT55905.2022.00010. **(Citations = 5)**
3. O. C. Williams and F. Olajide, "A Technological Approach towards the Measurement of Enterprise Agility," 2020 15th Iberian Conference on Information Systems and Technologies (CISTI), Seville, Spain, 2020, pp. 1-4, doi: 10.23919/CISTI49556.2020.9141142. **(Citations = 6)**
4. Williams, O., Olajide, F., Al-Hadhrami, T., Lotfi, A. (2020). Exploring Process of Information Systems and Information Technology for Enterprise Agility. In: Saeed, F., Mohammed, F., Gazem, N. (eds) Emerging Trends in Intelligent Computing and Informatics. IRICT 2019. Advances in Intelligent Systems and Computing, vol 1073. Springer, Cham. https://doi.org/10.1007/978-3-030-33582-3_98. **(Citations =5)**

Chapter 1: Introduction

Organisations have become very dependent on technological usage and its advancement in the 21st century such that, continuous evolution of technology has brought about challenges which are crucial for adoption. To remain competitive, organisations need to adapt towards change practices caused by digital transformation for effective decision-making. This can be executed by integrating through ad-hoc processes, Enterprise Agility (EA), which is the ability of organisations to adapt to changing environments, caused by technological and/or market turbulence.

Digital transformation procedure permits organisations to either modify or create new business models [1] thus, making it necessary for the implementation of emerging technological platforms. This uses the combination of human skills and Information Systems Infrastructure (ISI) in responding to change dynamics. Defined by [2] emerging technologies combine high expectations of technological and market uncertainty, and it proves to be a substantial substrate towards innovation breakthrough for industrial transformation. These include but not limited to Artificial Intelligence (AI), Big Data Analytics (BDA), Blockchain, Cloud Computing, Intelligent Automation (IA) Internet of Things (IoT), etc. In the context of this research, 2- emerging technologies BDA and IA were considered as they expedite analytical information for intelligent decision making, leading to performance based on profitability for customers satisfaction.

Big Data Analytics (BDA) supports pattern analysis recognition, and prediction, by using the sustenance of AI to automize processes for sustainability practices [3], leading to improved productivity, knowledge generation, and innovation upgrade [4]. This further aids improvement to promote new techniques of information and data gathered for business processes [4]. BDA can be utilised alongside Intelligent Automation (IA) as a holistic approach on digital transformation for change management practices in organisations. This can aid IA in its exploitation of various practices of virtualisation for accomplishing automated tasks, whilst involving humans and machine methods towards intelligent decision making [5].

Exploiting BDA towards the improvement of organisational performance has continued to receive high interest by academics and practitioners [6]. However, the use of an intermediate within the system can strengthen the underlying processes of strategic interoperability, therefore, increasing business process potentials for competitive advantages. This can be described as an added value to unprecedented and unpredictable situations caused by digital transformation [7].

With studies investigating the impacts of BDA for organisational performance [8]–[11], there is need for further investigation and understanding of complex behaviours and relationship between BDA variables and EA functionalities for enhancement of organisation's process-level and competitive advantages. This will improve customer's satisfaction based on productivity and performance level growth in service organisations.

EA is considered as an integrated intermediate to develop strategic and operational capabilities of organisation's internal and external structure in this research. It is additionally deemed for development of an application for service organisations using integrated Security Orchestration, Automation Response (SOAR) for EA calculation and analytical applications. The research study contributes towards service organisations in enabling agility for customers' satisfaction based on performance optimisation for productivity. Outcomes also provides insights to managers and consultants towards understanding and utilising enterprise agility for competitive advantages in uncertain situations caused by disruptive technologies.

The rest of this chapter is structured in the following manner: a background of research is discussed in Section 1.1 which is followed by the aims and objectives in Section 1.2. The problem statement is then identified in Section 1.3 and research questions based on contributing outcomes are identified in Section 1.4. The thesis structure is described in Section 1.5 and summary of this chapter is described in Section 1.6.

1.1 Background of Research

Emerging Technologies constantly impacts EA, and this has created a high dynamic business process infrastructural environment that constantly requires a swift adjustment due to complexity. Defined back in 2006 by [12], *EA is the ability of organisations to sense environmental changes and respond rapidly to it*. Measurement of organisation's EA level can help in understanding uncertainties and making predictive analytics based on complex dynamic behaviour of business process systems. It can also further be used for increasing speed based on decisions, support rate of achievement due to set targets and enhance customer satisfaction due to performance optimisation.

Though, it is evident that technology impacts performance of organisations positively [13], the use of an intermediate would enhances this process further.

Few studies such as [8], [14], [15] have considered using EA as a mediating effect towards performance of organisations. Also, most research are either theoretical or empirical and there is no thorough implementation of how agility can be measured in organisations. Therefore, it is quite necessary to develop an analytical application process which can enable managers and consultants measure its agility balance and understand its relational purpose and nature of complex behaviours in unprecedented technological environments.

This study uses a quantitative methodological approach based on positivism and defines 3-hypothesis to understand the relationship amongst the variables of BDA, EA and Cs and OP. It further goes ahead to understand the complex dynamic behaviour of these relationships, develop new metrics to calculate agility, and implement an analytical dashboard application using SOAR policies to help organisations understand its agile functionalities.

1.2 Research Aim and Objectives

This research aims at exploiting BDA and IA which are emerging technologies, to create an agile and effective technological platform for change management practices, operational stability, and digital transformation. This will focus on implementing an analytical dashboard application based on policies of SOAR technology. Although a novel approach when considering IA and EA, its improvement will lead to efficiency and efficacy of customer's satisfaction for performance optimisation and productivity.

To achieve this research aim, the following objectives for the research are considered:

1. Extensively explore concepts of emerging technology and business process impact for maximum operational stability, based on BDA, IA, EA, and OP. This involves proposing a conceptual model to exploit these influences.
2. Validate using Structural Equation Modelling (SEM), the patterns of correlation amongst variables of the model for Customers Satisfaction (Cs) based on performance optimisation and productivity in a service organisation of a developing country.
3. Develop an IA system for improved system capability for service request and intelligent decision making.

1.3 Problem Statement

Data-driven Information Technology/Information System (IT/IS) business processes aid in reducing complexity via the usage of BDA and IA for predictive analytics and forecasting. It is therefore necessary to implement through integration, a technological process that would support human skills and techniques of BDA capabilities whilst responding to change dynamics [16]. This process can support enhanced business system capabilities for intelligent and timely decision making.

The research problem occurs as academics and professionals recognised the significant impacts of emerging technologies on IT/IS infrastructures. This has brought about significant changes to organisation's business process models, and adapting to these changes will require evolvement of organisational infrastructure for process enhancement. This in turn can influence workload control and productivity for organisational performance based on profitability.

Previous research called for the integration of more data variables in organisational design models as the influence of BDA for organisational performance is not entirely clear [17], [18]. With possible data gathering from service organisations, the need for a causal dynamics' examination is required [19], as research have neglected ideas on quantifying BDA and it attributed capabilities. This will assist in optimisation of business processes towards equilibrium with the best impact factors of EA. This research study intends to analyse influences of BDA for digital innovation, predictive analysis for timely decision making, and organisational performance with respect to applied metrics for operational research based on profitability.

Prior to covid-19, service organisations in developing countries resisted the urge to completely go digitised or implement digital transformation within its business models. This is because they continued to rely on paper-based and in-person contact. However, the impacts of the pandemic changed working patterns, decision making processes, and organisations were hastily looking for evolving ways to implement digital transformation for performance optimisation and business reliance. In addressing these new patterns, service organisations therefore need to re-evaluate their operational strategies to stay ahead of the curve for competitive advantages and intelligent decision making. The utilisation of IA system for enhanced organisational capability scales up business process needs by reducing workload control and improving performance optimisation for profitability by providing an intelligent pool of resources for operability and intelligently enhanced decision making. It also can improve security awareness and performance in service organisations as it can automate incident management processes on service requests to create alerts for immediate authorisation and to control problem avoidance.

Intelligent Automation can be classified as peak priority in business process models of service organisations as it enables consistency of agile practices on immediate and automated responses to changes. It also enhances security awareness of organisations and helps drives a better satisfaction outcome for customers. Therefore, this research study considers the necessity of integrating IA as a holistic approach to agile business model infrastructures by developing an agile framework dashboard application to improve vital services for advanced customer experience. The application also optimises assured organisational platform based on automated security policies for data management and resource optimisation aimed at agile practices and change management.

1.4 Research Questions and Contributing Outcomes

This thesis answers three major research questions which is structured in a chronological order. Following the research aim and observed problems, the research questions are as follows:

1. *What factors influence emerging technologies for business process capability and how can they be utilised to attain maximum business operational performance?* – This question is based on an aspect of the research aim of the study which deals with exploiting emerging technologies for change management practices. Using a systematic approach, and based on theoretical views of existing literatures, the research question is answered in Chapter 2 whereby, moderators and mediators are considered in the application of emerging technologies as an ad-hoc for-business processes. It further aids hypothetical views of Chapter 3 which is considered for experiments and framework development. Key findings identify theoretical implications for practitioners and opportunities for future research, as it specifies organisational relevance of adopting an intermediate for strategic standardisations and interoperability in competitive environments.
2. *Are the underlying variable model of BDA and EA interrelated; and how can they influence Cs due to productivity and performance in service organisations?* – This is a prominent aspect of this research as related works have called for more exploration of the integration of EA as in intermediate for performance. In understanding the relationship and underlying variables of BDA, EA for Cs due to productivity and performance, this thesis aims to develop its hypothetical view

and use a Structural Equation Modelling (SEM) approach to observe interaction amongst each variable. Result outcomes and contributions are further discussed in Chapter 4 and Chapter 6 respectively.

3. *How can an intelligent system be developed to improve operational capability of organisations and how can strategic decision making be enhanced?* - Proposed as the main novel contribution of this research, answers to this research question "*RQiii*" investigates IA which peaks business models for competitive advantages and change management practices. It further develops an application which can be used in standardised service organisations to assist in measuring enterprise agility and enhance security awareness based on cybersecurity policies. Therefore, avoiding organisational vulnerability due to redundancy caused by human errors and adaptability to dynamic technological environments. Vital contributions of the research answers are discussed in Chapter 6, and this also addresses some research questions and limitations of related works in Chapter 2.

1.5 Thesis Structure

This thesis is organised into 7 chapters such that each chapter follows a procedure which is inter-related to the next and as described in the objectives and research questions above. The thesis structure is as follows:

Chapter 2: This chapter discusses background of relevant concepts including related works of Emerging Technology (ET), Big Data Analysis (BDA), Intelligent Automation (IA) and Enterprise Agility (EA) for Organisational Performance (OP). Using a systematic approach, it focuses on various concepts of mediating effects and its impacts for performance optimisation. It also investigates the concepts of IA for security awareness as well as the similarities between BDA and IA as considered emerging technologies for the research. A summary and contribution to academic knowledge and concepts for practice is also mentioned for adoption.

Chapter 3: This chapter discusses the methodological approach used for investigation in the research. Looking at several techniques, it reviews the research hypothesis, data capturing and measures, ethical measures considered, demographics as well as causal diagram of the research. Using a positivism approach based on quantitative assessment, it illustrates the research model as well as discusses a sample case study considered in research for service request in organisations. Furthermore, tools and concepts used in the experimental analysis are discussed.

Chapter 4: Presenting quantitative results and data analysis using Structural Equation Modelling, this chapter investigates the similarity amongst variable concepts of BDA, EA and Cs for productivity and performance. Path coefficient of each measured variable is illustrated, and it provides consistency and explanation of how each hypothesis represents the theory for adoption. Results obtained present and key findings to previous research limitations and pave way for an application development.

Chapter 5: This chapter focuses on the application design/dashboard of the research thesis. The application is developed using Oracle APEX and it considers IA platform for intelligent decision making and security awareness. The study further explores the Security Orchestration, Automation Response (SOAR) policies aimed at the research framework design for service request of business processes. Outcomes of the application provide key contributions for adoption in service organisations.

Chapter 6: An integration of key findings with regards to emerging technologies for organisational business processes is discussed within this chapter. It further shares insight on relative key findings and contributions summarised in each chapter of the research (Chapter 2, Chapter 4, and Chapter 5).

Chapter 7: This is the concluding Chapter of the research. It addresses identified issues realised and revisits answers to every research questions. It also discusses limitations of research, recommendations, and future works of the research. Final remarks are also noted.

1.6 Summary

It is imperative that organisations remain competitive whist adapting to technological turbulence due to digital transformation. This brings about the use of an intermediate such as EA, to speed up activities of organisational business process both internally and externally for sustainability and operability. This research considers 3-hypothetical views and using a positivism methodology based on quantitative analysis, investigates the impacts of BDA as an ad-hoc for EA. It also develops an application to assist service organisations in measuring its agility for competitive advantages and each objectives enables research contribution for practitioners as well as academics.

Chapter 2: Emerging Technologies (ET) and Its Impacts on Business Processes

2.1 Introduction

The need to adapt to changing environments is crucial towards organisational development in unprecedented situations, and this can be caused by either market turbulence or technological turbulence. Digital transformation has brought about technological disruptions, and to remain competitive, organisations need to be agile, whilst capitalising on using Big Data for emerging technologies such as Big Data Analytics (BDA), Artificial Intelligent (AI) for Machine Learning (ML), Natural Language Processing (NLP) for Intelligent Automation (IA). This aids valuable insights towards decision-making for intelligent business processes [20]. Improving its performance for customer's satisfaction based on business process, organisations can adopt the use of BDA and IA as emerging technologies as they deal with unexpected events of technology turbulence which causes disruptions to ISI. Using BDA as ad-hoc for empirical research further considered in this thesis, it is enables pattern analysis which creates sustainability practices and adaptation to any digital turbulent environment [21]. Also, (IA) exploits various practices of virtualisation for accomplishing automated tasks, whilst involving humans and machine methods towards intelligent decision making [5].

Emerging Technologies (ET) are new technological applications to whom its application to real world scenario has been largely unrealised. Classified into different types, its impacts on information system infrastructures and business processes increases profitability of organisations, making it affordable and scalable, whilst improving infrastructural integration and collaboration [22]. It assists with alignment of operational systems to improve Organisational Performance (OP), thereby enhancing procedures necessary for organisational readiness and business process delivery [23]. ET creates a massive impact on business process infrastructures such that organisations need to enhance its adoption rate to change management practices for a faster response to technological turbulence. However, in doing so, the integration of mediating factors "such as Agility" to improve operational and strategic potentials for competitive advantages and efficiency is required. This in turn can improve technological capabilities and enhance automation of organisational service business processes [4].

Anecdotal research has shown that Information Technology plays a significant role in enabling organisational performance [13]. However, recent advancements caused by digital transformation of technologies, has brought about evolvement of business models in unprecedented situations. An example is the Covid-19 Pandemic which was considered be a great danger to human life in the United Kingdom and rest of the world in March 2020, and its aftermath affected several organisational frameworks.

Referring to ET in the context of an ad-hoc, due to association with unexpected events, this Chapter identifies relevant theories that discusses the potentials and efficiency of the two considered ET concepts (that is BDA and IA process) for OP. It also investigates the potentials of mediating effects on performance optimisation and explores the potentials of IA for security awareness in service organisations. Exploratory outcomes will be useful to attain and enable maximum business operations for performance.

2.2 Procedural Approach

The concepts of mediating effects are first explored with regards to BDA and its effects on OP. This is then reviewed systematically using a protocol development based on proposed hypothesis and research questions. IA is relatively reviewed based on concepts of security awareness for agile practices and then compared with BDA as an ET concept. The research gaps are also identified, and a summary based on key findings, theoretical implications and concluding remarks are given. Figure 2.1 below illustrates the procedural approach as described above.

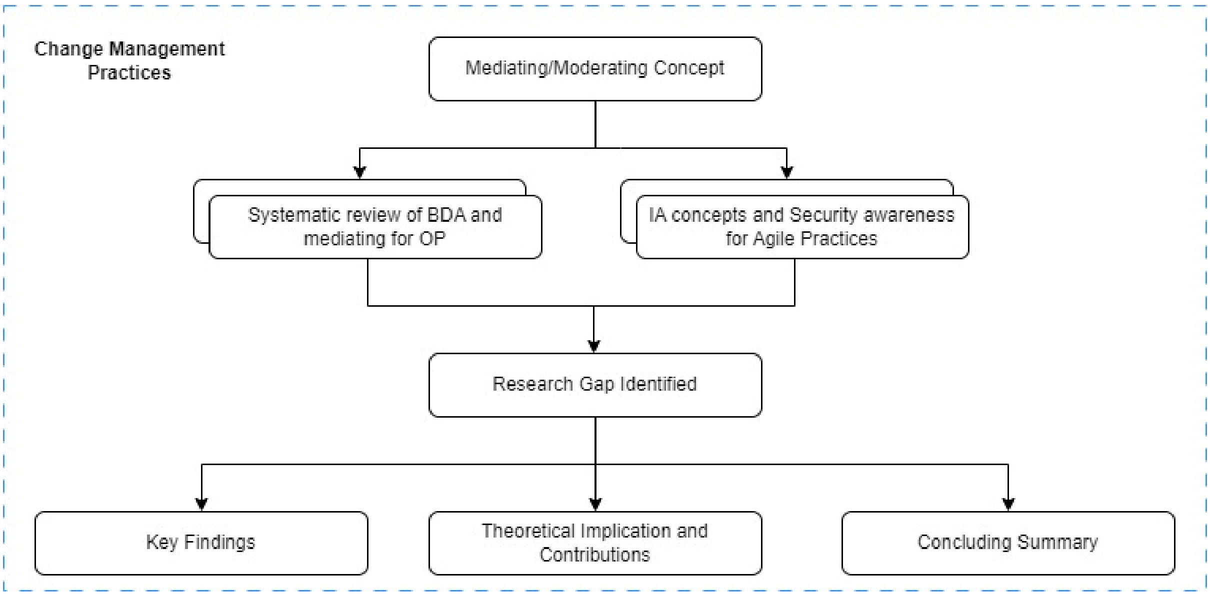


Figure 2. 1 Procedural Approach for Related Works

2.3 Mediating Effects and Moderators for Performance

Focusing on the perspective of BDA and OP, mediating effects, and moderators as a concept in organisational infrastructure creates indirect effects to strengthen underlying processes for an improved strategic operability in a digitally enabled competitive environment. Mediators and moderators can be associated to model development with regards to the researchers view and such include but not limited to dynamic capabilities, knowledge-based view, and resource-based theory, enterprise agility upon others. They are also regarded to as adding values to organisations in unprecedented and volatile situations caused by digitisation and external environments [7]. When compared to a moderately digital dynamic environment, its effects rely on exploitation of existing knowledge and its applications. Mediators and moderators can vary with regards to its utilising effect on entities regarded. Improving organisational performance, they facilitate digitization by using strategic and operational capabilities to enhance the competitive edge of an organisation in a technically turbulent environment.

2.4 Big Data Analytics (BDA) and Mediating Effects for Organisational Performance (OP): A Systematic Review

BDA is a technological platform that can transform organisational competition progress, by presenting new techniques to which information can be analysed for improved productivity, knowledge generation and innovation upgrade [4]. It can be used in descriptive, predictive, and prescriptive analysis for improved organisational performance and decision making. Comprising of 5- V characteristics, it enhances organisations for effectiveness, adaptability and flexibility in its performance [24]. BDA aims to build upon the analysis of large unstructured volume of data from several sources, such that its utilisation has become an increasing attention for academics and practitioners [6]. Therefore, leading to the utilisation of *"Agility"* as an external factor for adaptation to digitally turbulent environment.

Enterprise Agility (EA) is evident to be a competitive medium for organisations in a technically ambiguous environment. Initially proposed by researchers at the Iacocca institute (1991), and it is regarded as a key component towards sensing and responding capabilities of organisations to unprecedented technical situations [25]. In the field of Information Technology and Information Systems (IT/IS), EA is a medium that aids the drive of business processes, infrastructures, and performance in competitive unanticipated technical environments for better decision making. Thereby, supporting a rapid response to changes in an organisational system.

Focusing on the following hypothesis that is; [H1]- *"An increase in BDA improves the impact on the organisational agility"* and [H2]- "*An increase in organisational agility has a positive effect on performance"*; this section systematically reviews Information Technology and Information System (IT/IS) Literatures to discuss the positive impacts of BDA on organisation's performance, whilst considering EA as an intermediary. It should be noted that stable predictable markets based on organisations may limit the ability to support agility if little is at stake [26]. Therefore, this study argues based on the given hypothetical views and previous literature that BDA impacts OP positively if enterprise agility is considered in the business process model of the organisation.

2.4.1 Protocol Development

In developing a systematic literature review, guideline protocols following the Cochrane Handbook for Systematic Review of Intervention [27] was carried out. This involved the identification of research study aim and objects based on the research questions. Reviewing past literature and findings as related to Big Data Analytics, Enterprise Agility and Organisational Performance, each criterion followed an objective as related to the research questions.

2.4.2 Review Question

The review questions are based on "*RQi"* of the research study which states, "*What factors influence emerging technologies for business process capability and how can they be utilised to attain maximum business operational performance?"* This also considers the proposed hypothesis *[H1]* and *[H2]*. The research questions are as follows:

i. What are the factors that influence Big Data Analytics technology?
ii. How can Enterprise Agility be used as an intermediate between Big Data analytics and Organisational Performance?
iii. How does an increase in EA influence the performance of an organisation positively?

To answer these given questions, it is necessary to critically access previous literature to understand the concepts of BDA and EA for organisational performance. Answers to these questions will pave the way towards adaptability to turbulent environments in unprecedented situations as well as create given ideas in the field of research for organisational development in a digitally enabled environment. The methodological process follows the following outline illustrated in Figure 2 .2 below.

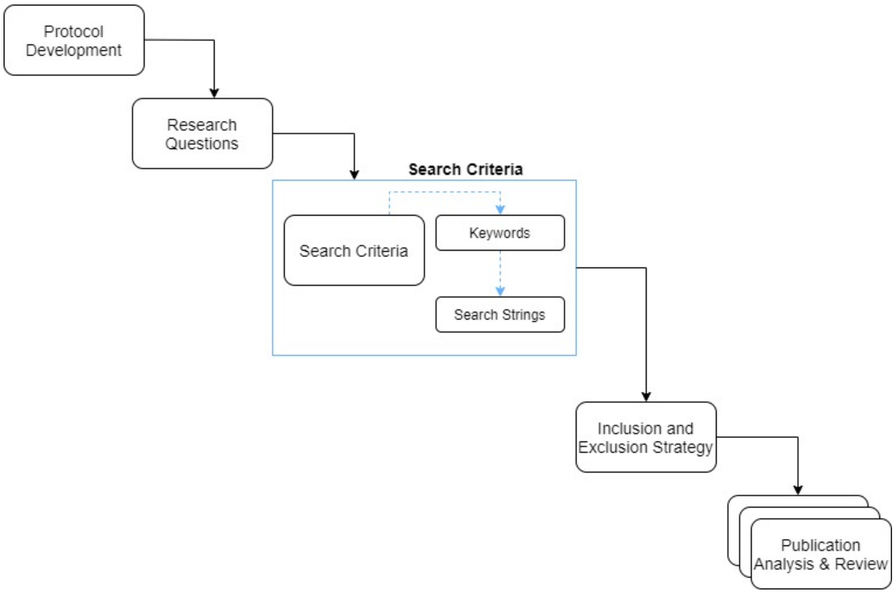


Figure 2. 2 Systematic Review Methodology

2.4.3 Search Criteria

The search criteria involved the usage of search strings and keywords to find as many literatures as possible in relation to the research study. Using a time span of 5-years (2016 -2021), the keywords used were divided into different concepts before including Boolean operations of "OR" and "AND" for the search strategy.

2.4.3.1 Keywords

Search keyword notions used in this research study is as seen in Table 2.1 below. Possible phrases and alternative keywords were used for identification to ensure an all-inclusive set of results were gathered.

Table 2. 1 Search Keywords

	Concept 1	Concept 2	Concept 3	Concept 4
Keyword 1	Big Data Analytics	Business Analytics	Data Analysis	Big Analytics
Keyword 2	Organisation Performance	Performance	Firm Performance	
Keyword 3	Enterprise Agility	Agility	Change	

2.4.4 Search Strings

In formulating a search string, and following the SCOPUS indexing system, the search was done over 3 different times, perioding from 2016 to 2021. The search followed the guidelines of [28]. The search terms "Big Data Analytics'' and "Organisation Performance" were the main search terms for the study. From the returned results, the term "Enterprise Agility" was added to ensure the documents considered were in relation to the research questions. Boolean terms "AND" and "OR" were used to ensure that other concepts in Table 2.1 were added to the search string. Limitations given were to ensure the search results gathered was within the years stated. The search string used is as follows:

(TITLE-ABS-KEY ("Big Data Analytics" OR "Business Analytics" OR "Big Analytics" OR "BDA" OR "Data Analysis")) AND (("organisation performance" OR "Performance" OR "Firm Performance")) AND ("enterprise agility" OR "Agility" OR "Change") AND (LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016)) .

2.4.5 Inclusion and Exclusion Strategy and Selection Criteria

Identifying the key documents to be reviewed, inclusive and exclusive criteria were performed. The search on the keyword concept of BDA as stated above returned a result of 394,920 documents. Upon addition of other keywords, the search returned a total of 30,719 documents.

Using the inclusion and exclusion strategy, the results were then further excluded to journal papers. This then reduced the total documented result search to 13,983 documents. A limitation to subject area was carried out and this included computer science, decision science, engineering, and business management, bringing the total documentation to 6474 documented papers. Before performing the accessibility criteria, journal source titles where screened and this excluded irrelevant journal titles not related to the field of research such included but not limited to molecular science, leaving a total of 599 papers to be screened.

Accessibility criteria was also considered during document selection to ensure there was no limitation to the papers. The titles as well as contents based on abstracts were also accessed with respect to its relevance to the topic of study. A total of papers 48 were reviewed.

2.4.6 Analysis of Literature

The literature analysis performed was based on selected papers with regards to its relevance to the research topic. Document types were either journal articles or peer review journal papers. Results revealed major articles on Big Data Analytics for organisational performance were from Business Information and Management, Computer Science and Decision Sciences. Other subject areas included Economics, Energy, Engineering, and Mathematics. With a focus to understand the impacts of BDA on Organisational Performance using a mediating effect of Enterprise Agility, this review investigated key variables, mediators, or moderators if any, arguments, findings, and study approach done by prior research to justify its hypothesis as well as answer the given research questions.

2.4.7 Research Approach on Big Data Analytics (BDA) and Organisational Performance (OP)

Table 2 below categorises, and analyses published journal papers in accordance with year published, Theoretical lens, approach used and mediating effect if any. This helps to understand the theoretical concepts of BDA and its contributions to organisational performance using a mediating or moderating effect. More so in understanding the antecedents of BDA and EA, this study will contribute to the growing knowledge and adoption of business analytics for organisational efficiency, competitive edges, and value creation.

2.4.7.1 Publication Distribution

The research publications were selected from the year 2016 to 2021 and this resulted into 48 studies. Out of these studies, five (5) are from the year 2021 as at April, whilst 19 studies are from the year 2020. More so, 13 studies are from the year 2019, and 5 from 2018. As detected, with each passing year, there is an increase on publishing articles of growth focus with respect to BDA for OP in reputable journals. This has been sub-divided into Tables 2.2 to Table 2.6 with regards to mediating/moderating effects. However, studies in Table 2.6 have not incorporated any mediators but discuss on the impacts on BDA for OP with regards to respective research.

2.4.7.2 Review on Mediating Effect

It is noted from exploring literature that few studies have considered a mediating effect/moderating effect for performance optimisation in organisations. Table 2.2 below reviews 3- publications [8], [14], [29] have used agility as a mediator. These studies based on their key arguments and findings suggest BDA capabilities applications influence organisational capabilities with reference to EA. Thereby effecting a better performance through a high-enhanced decision-making.

Table 2. 2 Enterprise Agility as a Mediating Effect

Author & Year	Theoretical lens	Methodological Approach	Type of mediating or moderating effect
[14], 2018	Resource-based view and IT business value literature	An interpretive qualitative approach was considered with empirical analysis on a comparative case study of 3 manufacturing companies with varying level of BDA usage.	Agility
[8], 2017	Knowledge-based view and dynamic capabilities	Based on a conceptual model, the research study used a survey on multi-country of European organisations from several industries with a total 175 usable responses and PLS for data analysis.	“Agility” mediating the between knowledge assets and performance.
[29], 2019	Dynamic capability views	Data was gathered from sample European managers with the help of UK-based marketing research and analysed using descriptive statistics and correlation analysis.	“Agility” and “organisational ambidexterity” mediates the relationship between BDA capabilities and Organisational Performance.

Environmental dynamism also played a key role to research studies on BDA for OP. Table 2.3 illustrates review literatures that considered environmental dynamism as a mediator/moderator. [30] used environmental dynamism as a moderator and argued that digital platform capabilities were antecedent to BDA dynamic capabilities for service innovation. This is in relation to research by [31] whereby the study used environmental dynamism to investigate empirically proactiveness and innovativeness to dynamic markets. The research further argued environmental dynamism was conducive to entrepreneurial orientation and had a significant effect on BDA operational performance. Also, [32] based on statistical analysis, described IT capabilities with regards to BDA-enabled dynamic capability, influenced operational performance highest if environmental dynamism was kept moderate. Merging environmental dynamism with environmental munificence, [33] stated BDA solutions enabled entry of organisations to new markets, whilst satisfying customers.

Table 2. 3 Environmental Dynamism as Mediating Effect

Author & Year	Theoretical lens	Methodological Approach	Type of mediating or moderating effect
[30], 2020	Dynamics capability view	With regards to 5-hypothetical view, and proposing a research model, a questionnaire was developed and analysed using empirical evidence from 175 organisations in China.	Environmental dynamism as a moderating effect.
[34], 2020	Dynamics capability view	Based on its hypothesis and building a hypothetical model, a survey with 281 responses was gathered using a pre-tested questionnaire. This was then analysed using PLS-SEM and covariance-based SEM.	Environmental dynamism.
[31], 2020	Dynamics capabilities view and contingency theory	A model was developed and using a research survey of 256 responses, the model was validated using Warp PLS 6.0, which is a technique used for path analytical models.	Environmental dynamism as a moderating role.
[33], 2020	Contingency theory and resource-based view	Using a combination of cross-sectional survey data and secondary data from sample medium and large companies, the empirical model developed based on the hypothesis. This was tested using regression.	Environmental dynamism and environmental munificence as moderating effects

Table 2.4 below shows knowledge management as considered by both research studies. [35], [36], used knowledge management as mediating effects on BDA for performance. Following a theoretical lens approach, each research study used empirical reviews for data collection on SMEs. It further stated there was a positive effect of BDA capabilities that improved decision-making and organisation performance.

Table 2. 4 Knowledge Management as a Moderating Effect

Author & Year	Theoretical lens	Methodological Approach	Type of mediating or moderating effect
[36], 2018	Resource based view theory	Using an empirical analysis based on structural equation modelling, data was collected from 88 Italian SMEs. This was validated using elliptically reweighted least square methods as estimation procedures.	Knowledge management.
[35], 2020	Resource-based theory	The study proposed a research model and data was collected from respondents in SME and through an adapted instrument. Using a 5-point Likert scale, the data was analysed using regression analysis.	Knowledge management practices.

Other studies as shown in Table 2.5, have incorporated different mediating effects such as innovation, organisational absorptive capability, knowledge absorptive capability, governance, circular economy, BDA, organisation culture and organisational flexibility.

Table 2. 5 Review of other mediating/moderating effects for BDA on OP

Author & Year	Theoretical lens	Methodological Approach	Type of mediating or moderating effect
[32], 2017	Resource-based view and literature on BDA	Proposed a research model using RBV and socio-materialism theory. Using positivist approach, a survey was developed with 315 responses and validated using Partial Least Squares (PLS) based Structural Equation Modelling (SEM).	"Process-oriented Dynamic Capabilities (PODC)". This mediated BDA capability on Firm's Performance with a z-statistic of 3.19
[37], 2017	Resource-based view and dynamic capability	A survey method was implemented, and data was gathered from hospitals in Taiwan with 155 responses. Structural Equation Modelling was used for testing.	Knowledge absorptive capacity
[38], 2019	Dynamic capability	An empirical model was developed with an emphasis on Business Analytics use in Customer Relationship Management (CRM). 170 samples were gathered from a firm level survey.	"Customer response capability" partially mediates between business analytics use and CRM performance.
[39], 2019	Information and innovation capability	A conceptual model is proposed and a survey with 154 companies is constructed. Partial Least Squares/Structural Equation Modelling is used to analyse the data	Moderating effect of technological and market turbulence.
[40], 2019	Dynamic capabilities view and contingency theory	Building a theoretical framework, the author used a survey data from automotive components manufacturers collected in 2015 to test its hypothetical model. Analysis was done using Warp-PLS software on several defined variables.	Organisational flexibility
[41], 2019	Resource based view	Building 3-major constructs from its hypothetical view, a research framework was designed. Data was collected from 600 companies and analysed using partial least squares	Organisational absorptive capability

[42], 2020	Resource based view	Based upon theoretical analysis of literature, the study developed several hypotheses. A survey was conducted using online portals and analysed empirically using SPSS 23.0 and Amos 23.0	Green innovation
[43], 2020	Dynamic capability view	The study used a quantitative analysis approach. A survey was carried out from tech start-up companies in India and China. Warp PLS 6.0 was used for analysis and testing of common method bias, endogeneity, and data reliability	Innovation
[44], 2020	X	A sample survey or 321 responses was collected from 106 Indian manufacturing SMEs, and this was analysed using exploratory factor analysis, confirmatory factor analysis and structural equation modelling	Big Data Analytics
[45], 2020	Knowledge management and dynamic capability theoretical lens	A research model was proposed and, the study carried out a survey from American and European firms that use IoT and BDA. The results were analysed using Partial Least Squares	Moderated by firm's process sophistication
[46], 2020	Resource-based view, dynamics capabilities view and literature on BDA	To test a proposed research model, survey data was collected from 202 Norwegian firms and analysed using Partial Least Squares and Structural Equation Modelling	Dynamic capabilities
[47], 2020	X	The study was based on an empirical survey of 350 supply chain managers from an Indian retail industry. Analysis was dine using Structural Equation Modelling to validate its results.	Governance as a moderating variable
[48], 2020	Absorptive capacity theory	The study developed a research model which is tested using a questionnaire survey of 218 businesses in the UK	Environmental scanning
[10], 2020	Dynamics capabilities view (resourced-based theories) and socio-materialism	The study used a positivist and deductive approach. Using a survey questionnaire with a 5-point Likert scale, data was collected from different sources of IT professionals. Analysis done included exploratory factor analysis and confirmatory factor analysis using SEM for testing	Organisational culture
[49], 2020	Resource- based view	In examining its research model, a survey data collected from 175 IT and business managers was analysed using partial least squares and structural equation modelling	Information governance as moderating effect
[50], 2020	Social capital theory and knowledge-based dynamics capabilities	Following a deductive approach and quantitative techniques to test its hypothesis, data was collected from China in providing context of an emerging economy. Structural equation modelling was used to employ its hypothesis	BDA capabilities as mediating effect and a moderation role of data driven culture
[51], 2021	Dynamic capability view	An empirical study on 320 manufacturing firms in India was conducted to investigate the relationship between BDA capabilities and sustainable supply chain performance. Analysis was done using partial least square structural equation modelling (PLS-SEM)	Circular economy (CE) practices and sustainable supply chain flexibility

[52], 2021	Dynamic capabilities view (DCV)	The research used a survey data from UK firms. It proposed a model which was accessed by PLS-SEM (symmetric) and fuzzy-set qualitative comparative analysis method (asymmetric).	Entrepreneurial orientation
[53], 2021	Institutional theory and resource-based view	Using a statistical approach and a 5-point Likert scale, the research proposed a theoretical model, and its hypothesis was tested using PLS-SEM based WarpPLS version 6.0 software.	Organisational flexibility and industry dynamism

Some research studies haven't used any mediating/moderating effects in their studies as shown in Table 2.6 below but insist that BDA has a positive effect on OP based on various studies.

Table 2. 6 Studies without mediating/moderating effect for BDA on OP

Author & Year	Theoretical lens	Methodological Approach	Type of mediating or moderating effect
[54], 2016	Resource-based theory	Used 2-pilot studies and survey data to empirically validate the relationship between BDA capability and firm's performance.	X
[17], 2016	Resource-based theory	Measures of research were used from existing literature on BDA. Pilot survey was conducted with 61 respondents from a BDA group on LinkedIn. Survey items were measured on a 7-point Likert scale.	X
[55], 2017	Resource-based theory and capacity building	Content analysis was employed for testing research validity as data was collated from 112 case descriptions.	X
[56], 2018	Practice-based view	Using Interpretivist paradigm, a multiple case study was investigated as data was collated from materials to explore values of emerging technology.	X
[57], 2018	Resource-based view theory	Questionnaires were sent to a sample of French companies with over 200 questionnaires gathered and data analysis was done using a variance -based structural equation modelling.	X
[58], 2018	X	A theoretical analysis of potentials BDA-capable business process management system in increasing organisational agility with regards to ambidextrous organisations was executed. This gave rise to a conceptual framework.	X
[59], 2019	X	Using a mixed-method approach, a Delphi-study was done to explore the antecedents affecting BDA development. An empirical model was proposed and validated by a survey on 17s European firms.	X
[60], 2019	Complexity theory	Follows a mixed-method approach using survey from 175 chief information officers and IT managers in Greek firms. The research builds upon 3 case studies and uses fuzzy set qualitative comparative analysis method for its quantitative data	X
[61], 2019	Literature review	Building upon a conceptual framework, Questionnaires were developed based on hypothetical views and a pilot testing of data was carried out. Statistical analysis was done using SEM which was given to Artificial neural network for discussion	X
[62], 2019	Literature	The authors used an empirical qualitative analysis, with marketing managers of 4-retailers in Italy and secondary data to get a better picture on how big data is deployed into organisations	X

[63], 2019	Coordination theories	Proposing a theory on information quality to assist having business value, user satisfaction and firm performance, and designing an appraisal-emotional response-coping framework, a survey was carried out on a leading research firm with 302 responses and analysed using PLS-SEM	X
[64], 2019	Systematic literature review	The study used a qualitative methodology on a systematic literature review, thematic analysis, and semi-structured interviews	X
[65], 2019	X	Using an inductive approach, the study used a qualitative approach by conducting semi-structured interviews with senior managers and analyst in oil and gas companies across 8-countries. This was analysed with Atlas's software.	X
[66], 2020	Dynamics capabilities view	8-selected case studies of operations research activities in large organisations were considered, of which each invested significantly in implementing analytics technology	X
[67], 2020	Dynamic capabilities	The study empirically investigates BDA capabilities and its influence on organisational flexibility. Data was collected from a distributed survey to 215 managers in European companies and this was analysed via testing with Structural Equation Modelling.	X
[11], 2020	Resource-based view and dynamic capabilities view	The study used an integrated multicriteria decision-making (MCDM) methodology across 3-stages. That is Intuitionistic fuzzy decision-making trial and evolution laboratory (IF-DEMATEL), analytic network process (ANP) and simple additive weighing (SAW)	X
[68], 2020	Resource based view, dynamic capability theory and emerging literature	Building a research model and using an online survey, the study gathered responses form service system analytic managers and applied common method variance. Data was analysed using Smart-PLS 3.0 for structural modelling estimation.	X
[4], 2020	Resource-based view	The research study used a survey questionnaire in collecting data. Using a 5-point Likert scale with several constructs, 171 usable responses were analysed using Partial Least Squares (PLS).	X
[20], 2021	Research findings	The research proposed a conceptual framework and used grounded theory to understand and define an empirical interpretation of big data methodological approach in organisational competitive intelligence (CI) cycle	X
[69], 2021	Organisation information processing theory	Building a conceptual model, a survey was carried out from 168 hospitals. Data was analysed using partial least-squares and regression based structural modelling method	X

However, some research such as [30], [35], [43] called for the investigation into other mediating and moderating roles to improve organisational response to speed, as well as its infrastructural capabilities to enable competitive advantages.

2.4.8 Enterprise Agility (EA): An Effective Mediator on Big Data Analytics and Organisational Performance

Enterprise Agility creates an avenue for digital and other emerging technologies such as BDA and IA to expedite technological establishment [70] for performance optimisation capabilities and enhance decision-making for business processes. When introduced into Information System (IS) structures of organisations, it acts as an intermediate between

BDA and OP by positively enhancing internal information processing and accelerating internal innovation for competitive edge. EA also encompasses organisational capabilities both internally and externally. The deployment of EA enables organisations' proactivity to changing environments caused by digital technologies or market dynamics. Figure 3 below, establishes direct and indirect effect of BDA on OP as EA acts as an intermediate.

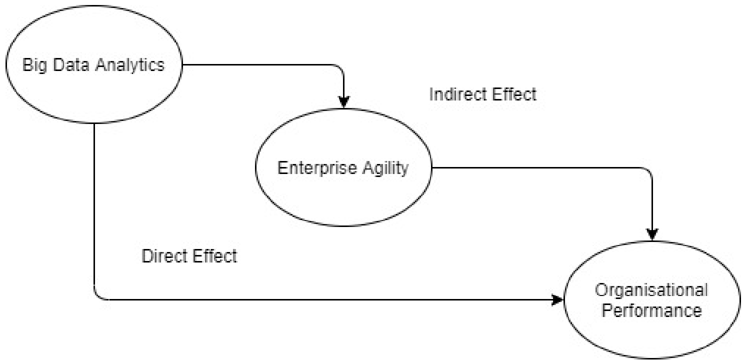


Figure 2. 3 EA as a Mediating Effect

In responding to research question (ii) of Section 2.4.2, Figure 2.3 illustrated above can be used to develop hypothesis in responding to RQ (iii) of the same section. Previous research by [8], [14], [29]; employed agility as an intermediate for organisational performance, and it was deduced that EA enabled competitive advantages via the enhancement of value performance and enablement of organisational ambidexterity in a complex technological business environment.

2.4.9a Enterprise Agility (EA) implementation for Organisational Performance (OP)

The implementation of a mediating effect enables faster response as internal and external business processes are accelerated to complex situations. It is evident that digital technologies create a positive impact on organisational performance using digital organisation culture [71]. Hence, it can be deduced that EA supports adaptation to change management practice; therefore, enhancing Customer Satisfaction (Cs) for performance optimisation and productivity. Focusing on business process infrastructures, EA uses available resources to exploit varied capabilities of BDA and OP. It creates an increase in sensing and responding capacities through technological influence. This process brings about proposed hypothesis *[A1]* which is, *"an increase in the sensing and responding capability of an organisation, increases its performance positively through business processes."*

In delignating *[A1]*, accumulated impact of BDA capabilities on specified business processes for system development enables efficient implementation of IT/IS services in technological ventures. This can be expressed based on the application of EA for performance due to profitability and productivity. It supports demand fulfilment of service level agreements by optimising Cs, such that business process features could be integrated with agile principles and manifestos [72] for performance augmentation.

2.4.9b Big Data Analytics and its enabling role for Organisational Performance

BDA capabilities have been defined by several researchers and practitioners and it is referred to the tools, techniques and processes required for data-driven decision making through planning, organisation, visualisation, and analysis [73]. Using a dynamic capability view, BDA capabilities are classified into tangible (data, technology, and basic resources), human (managerial skills and technical skills) and intangible (data-driven culture and organisational intensity based on learning abilities) resources [54]. The deployment of BDA capabilities improves OP through integrated and assembled data-based resources. These form aspects of BDA characteristics and gives insight to data management infrastructure for organisational transition of better competitive advantages [21]. Exacting competitive gain for performance enhancement and change management practices, BDA capabilities create positive impacts, as its supports organisations in creating a sustainable environment irrespective of unprecedented situations. Furthermore, BDA capabilities are influenced by knowledge application sources and organisational activities [50], and a lack in the integration of both internal and external organisational data could lead to a less-likely competitive edge.

Data quality leverages BDA capabilities [45], due to its representation of information processing for knowledge creation and innovation for technological proficiencies. This develops swift adeptness to changes on marketing strategies and management of supply chain [29]. In large organisations, BDA capabilities continually remains a structural aspect in the pursue of data infrastructures for technological and market dynamics. It should be noted that without BDA capabilities, organisational adaptation to change management practices is limited.

2.4.9c Big Data Analytics and Enterprise Agility for Organisational Performance

Over the past years, BDA for OP has shown a significant growth of importance to academics and practitioners. Precious research described a positive effect of BDA and EA on OP. Thus, it is pertinent to understand relevant ways studies have shown influences of BDA, EA, and OP.

Investigating improvement of organisational performance using BDA capabilities and business alignment strategies [17], research findings showed BDA capabilities consisted of 3 primary dimensions which are management, technology and talent capability. The research also deduced there was a strong effect of BDA capabilities on organisational performance. Limitations called for the integration of more variables such as business process agility and process-oriented dynamic capability to be included into its design model using a 7-point Likert scale. Likewise, [32] proposed a model and examined the direct effects of BDA capabilities on firm performance. The research considered dynamic capabilities and followed a resource-based view survey approach. It concluded that the higher order of big data analytics capability construct had a stronger effect on organisational performance. Research by [74], used a theoretical approach and attempted to explain market performance with regards to BDA impact. The research study concluded both social media diversity and BDA had a positive interaction effect on market performance as BDA created values in conjunction with several ETs.

Developing a research model on resource-based view and competitive strategy theory, [75] attempted clarifying Software-as-a-Service (SAAS) with regards to a case study influenced by firm's performance through the firm's capability, The study concluded that capabilities adopted by SAAS enterprise application positively impacted the concept of business value. This in turn positively impacts the firm's performance. Though the research argued the importance of applying a mediator construct. It further called for validation of empirical result and testing of its study in a different continent.

2.5 IA Concepts and Security Awareness for Agile Practices

Enterprise Agility (EA) stimulates rapid responses towards changing circumstances caused by technological innovations and classified as a change management practice towards organisational sustainability. With the advent of digital transformation, ET continuously brings about disruption to organisational business processes and it is necessary to implement via integration, a technological process that would support human skills of BDA capabilities in responding to change dynamics.

Digital transformation aids Robotic Process Automation (RPA) for dynamic business processes, such that it improves ISI infrastructure via human behaviour automation [76], for performance optimisation. This permits work quality and eliminates human negligence with increased reaction time [77]. Establishing repetitive and autonomous task, RPAs emulate humans by using Artificial Intelligence (AI) methods on an intelligent software [78]. It further improves dynamic environment centred on Return on

Investments (ROI), for cutting cost through implementation for effective decision-making on business processes and profitability.

Aiding improvement of systems infrastructure using human behaviour automation [76], Intelligent Automation (IA) exploits various practices of virtualisation for accomplishing automated tasks, whilst involving humans and machine methods towards intelligent decision making [5]. It involves the integration of RPA and AI for improved technological capabilities [79] and automation of organisational service processes. IA can be described as a holistic based approach on digital transformation for automation of manual activities towards faster response rates. It comprises of several rudiments of ETs such as such as Business Process Automation (BPA), Internet of Things (IoT), RPA, AI, and BDA. Exploiting several opportunities of EA for competitive edges and change management practices, IA aids business models especially in service organisations for prompt responses and fixations of service requests. These however, come with several security risks and threats which need to be avoided to eliminate redundancy.

Automating human driven processes in service organisations on repetitive tasks enhance decision making intelligently, giving rise a more robust system architecture. Although, its innovative aftermath contributes towards complexity of ISI based on malicious targets, thereby leading towards the implementation of automated cybersecurity solutions [80]. It is therefore necessary to implement secured authentication in service organisations that can act swiftly to cybersecurity breach whilst still practicing agile change management for competitive advantages.

2.5.1 Intelligent Automation (IA Concepts)

Intelligent Automation (IA) in organisations is vital as it is an ET notion that incorporates Artificial Intelligence (AI), Machine Learning, and dynamic workflow to aid end to end business processes automation for digital transformation hastening. It can be described as an automated process that practices virtualisation of intelligence for achieving automated task, whilst involving human and machine methods for intelligent decision making [5].

Defined by [81], it is described as *"the application of AI in ways that can learn, adapt and improve overtime automated tasks previously done by humans".* IA is also discussed to support business process efforts [82], as it serves to be a critical aspect of digital transformation [83]. The use of IA in a complex dynamic organisational environment improves accuracy and productivity for strategic focus and operability. This will therefore enable scaling up agility for business service continuity. IA encourages exponential value through adaptation as an adoption for business processes would enhance model development for effective decision-making in unprecedented situations.

In prioritizing security awareness of IA systems in service organisations, it is best to automate incident management processes on service requests to create alerts for immediate authorisation and to control problem avoidance.

2.5.2 Security Automation

Information security standard is seen as a complicated issue as applied to security management and organisations are faced with evolving cyberthreats which causes security breaches. Security Automation deals with the utilisation of IA platform to connect and orchestrate several security tools for research to cope with security alerts and deal with false positives. Research by [84] states cyber-defences must be agile towards voluminous vulnerabilities, and persistent threats for effective business functions. [85] defines security automation as "the use of information technology in place of manual processes for cyber incident responses and security event management". Furthermore, [86] defines it as "an automation handling task in a machine-based security application that can be done professionally or by a cybersecurity professional". This can be used in incident processes of service organisations as it helps to eliminate time consuming administrative processes as well as reduce human-errors and meantime to recovery errors whilst making service organisational processes more efficient and dependable.

2.5.3 Security Orchestration, Automation Response

The use of Security Orchestration helps towards the planning, integration, cooperation and coordination of security tools and expert activities for the production and automation of incident response to actions required in security threats [85]. According to Forrester reports by [87], it is crucial to integrate both security awareness and security orchestration together creating Security Orchestration, Automation Response (SOAR).

SOAR enables technology integration of persons and process as people are responsible for intelligent based decision making, while technology used is for streamlining complex processes [88]. It can be described to offer an ideal solution for organisations in addressing security challenges as SOAR uses technologies of AI, Machine Learning (ML), deep learning, automation, threat intelligence and orchestration [89]. It further enables deployment on incident response processes of organisational service request by utilising a piece of code or script. The implementation of SOAR on agile practices of service organisations enables quality attributes of integrability, interoperability, interpretability, flexibility, and usability and this is related to attributes of both IA and EA for competitive advantages and intelligent decision making.

2.5.4 Security Awareness, Intelligent Automated Systems and Service Organisations

Improving business processes of service organisations, privacy and security are major concerns to organisations. The implementation of security automation helps aim at cutting down high number of routine checks and incidents [90]. Based on this effort, service quality and incident responses can be improved leading to business growth and competitive advantages. A lack of automated security practices on service organisations, could lead to poor protection against threats. Therefore, it is essential to implement an essential cybersecurity management process to improve data reliability, security intelligence and security posture for business processes.

Evaluating Information Security Continuous Monitoring (ISCM) for security automation, [84] developed a conceptual framework in a DoD organisation. Using quantitative studies, it identified current states of ISCM, and role of security automation based on change required for enhancement and automation leverage. The study discussed techniques of improving ISCM capabilities to satisfy requirements based on security automation for rapid response action. It further identified ongoing research work to refine its proposed framework as the research outcome was not an audit of compliance with policy nor vulnerability nor risk assessment.

Investigating an architecture-centric support for integration of security tools in a secured orchestration platform, [88] presented support towards the design of SOAR platforms. The research used a conceptual map of SOAR platform with key dimensions of architectural design space. It showed proof of concept based on automated integration of security tools as well as automated interpretation of activities for the execution of incident response processes. The study described its approach to have laid a foundation for future research based on its design and deployment of SOAR platforms. It further discussed that further research work was to consider a larger-scale mapping for architectural design decisions on pattern generation.

Using an interdisciplinary literature review approach, [91] investigated the strategic impacts of IA for knowledge and service work. Conceptualizing IA with associated technologies and providing a business value-based model of IA for knowledge and service work, the research identified twelve research gaps that hindered understanding of business values towards prospects of realisation. It stated appropriate level of automation tasks involved microlevel variation to influence performance of organisations as a research gap. It further asserted socially acceptable values needed to be designed for Intelligent Automation, to enable ethical decision making and testing requirements for adoption.

A survey conducted by investigating various papers and work done by both academic and industrial practitioners, [85] used a multi-vocal viewpoint to understand future research directions of AI/ML in Security Orchestration, Automation and Response (SOAR). The study concluded that an urgent need for propping cyber-defence operations with advanced orchestration was necessary for automation capabilities towards an effective and efficient cyber-defence for advanced dynamic cyberthreats in service organisations. Furthermore, the study explained deep reinforcement learning algorithm needed to be explored for SOAR by identifying research on SOAR was still as nascent stage. It also advised further research work was required for the integration of ontology development into AI/ML SOAR systems for interpretability and interoperability of security tools developed by solution providers.

Investigating software security patch management, [92] used a systematic literature review and identified future researches on socio-technical challenges in regards to reported solutions, evaluation and industrial relevance of the reported solution for complex systems. Using a snowballing method to review literatures, the research discussed fourteen socio-technical challenges in software security patch management and eighteen solution approaches. It described there was a need for Human-AI collaboration for software security as complex tasks could be achieved through hybrid intelligence. The study further stated that intelligent system with real-time, human like, cognition-based framework could guide autonomous decision making of practitioners by providing then with timely information and help with logical questions.

2.6 Key Findings of Related Research

Despite research publications on BDA for OP and grounded on theoretical lens, it is observed that studies incline to investigate avenues for organisations to exploit its resources to achieve a sustainable competitive edge. Also, resource-based views and dynamic-capability views continue to be the major focus during reviews.

Exploring findings on BDA for organisational performance, BDA capabilities provide positive associations, in regard to its constructs [17]. It can be built on organisations infrastructural architecture for value inclusion [55], decision making processes and competitive advantages. Furthermore, BDA enables exploration of business processes in supply chain, value chain, financial regulations, Cloud Computing, Software-as-a-Service, and information service requests, for improvement on its analytical capability via implementations to organisational structural systems. Internal capability of organisational cultural practices [10] improves structural competence of BDA and increases performance gains, leading to data-driven organisational culture. Therefore, improving technical skills via workforce adoption and sustainable change management practices of BDA for OP.

Knowledge management procedures grounded on applications of BDA can help in triggering EA for improved competitiveness. This can be achieved by intelligently implementing through dynamic orchestration [93] ISI's for strategic and operational capabilities for performance advantages. Thus, aligning integrated agile information systems infrastructures using cyber-physical techniques, and based on policies and incident responses to complexity [23]. It is therefore essential for organisations to practice and ensure IA systems are revised for secured rapid response to internal and external change agents. This would encourage higher performance optimisations and better utilisation of BDA resources.

Intelligent Automation (IA) in service organisations help to improve agility and change management as it supports workforce agility in responding to dynamic changes. It is also vital to encourage and improve security awareness to reduce vulnerability to security threats and boost business performance functions for competitiveness. According to [94], transparency in organisation's infrastructural systems can occur through effective task monitoring of automated IT service process. However, it would require a secured platform for effective sustainability and enhance risk-based decisions based on situational awareness.

Security awareness enablement for service organisations enhances mean time to respond (MTTR) on incident processes. It also enables mean time to detect (MTTD), hence, improving organisational agility which is the ability to detect and respond to changes. As organisations are faced with dynamic situations, it is vital that security policies are enacted towards trustworthiness. This could include the implementation of Access control, Authentication and Authorisation (AAA) and should be managed by the CSIRT management. SOAR platform facilitates detection and trigger actionable security operations by sensing threats, delegating tasks and automating remediated actions [85]. It further supports activities based on case management via report logs whilst enabling automation of manual repetitive task processes in service organisations. SOAR embedded in organisational system permits monitoring of activities across service system request, as it support intelligent decision based on secured end-to end management.

2.7 Gaps Identified

It is evident that the search for adaptability to changing environments is crucial, as organisations seek advantages to remain competitive in emerging digital markets. However, security issues and threats pose serious challenges during technological turbulence adaptation using change management principles for disruptions caused by digital transformation.

Although studies aim at providing relevant solutions for practitioners, it is necessary to develop a dynamic system model to understand using exponential form, agility levels for change management practices and competitive edges. Also, focusing on limitations and further works of previous studies such as [6], [32], [75], the integration of additional variables such as business agility and validation of hypothesis based on constructs of BDA and EA impact for Cs based on productivity and OP is required to understand the inter-relation amongst each variable for organisational adoption and enhanced decision making.

IA improves business process adaptability to disruptive technological environment by automating repetitive task and enhancing agile functions of sensing and responding capabilities for intelligent decision making and reliable processes. As denoted from previous literature, IA is still at nascent stage, therefore research is on its application is limited. Integrating a secured platform based on SOAR principles into an agile model for the implementation of an intelligent automated dashboard application is vital for service organisations request process. Outcomes will assist in validation of framework design useful for adoption in business processes to improve customer experience and help in competitive advantages.

2.8 Theoretical Implications & Contributions

Based on research findings, this research section has contributed theoretically towards practice implementation for organisational performance. It provides relevant theoretical evidence, on the positive relationships between BDA and OP as this will assist organisations in effective decision making with regards to business processes in a complex environment. Also, it shows that with the effective use of a moderator/mediator such as agility, the ability to speed up operational processes is inevitable. This will improve change management and support adaptation of business processes for IT/IS infrastructures of organisations.

This contributes towards academic and professional literature for research purposes as it has systematised existing knowledge on BDA for OP with regards to theoretical lens research approach, and mediating effects. It is agreeable that BDA utilisation for performance advantages in a complex digitised environment can enable organisational innovation and adaptability for practise [9]. Therefore, this research recommends future exploration on the following topics for forward-thinking research opportunities.

1. Cloud-computing and BDA for performance advantage purposes in a disruptive organisation.
2. Intelligent Automation on BDA in a post-pandemic era.
3. Mediating effects on business processes with regards to complexity due to digitization and market disruption.
4. Implementation of an effective information system architectural design for business intelligent operations.
5. Cyber-security policies and practices using BDA approach in a disruptive environment caused by emerging technologies.

Research opportunities can provide further functional insights on BDA adoption into organisations, for strategic standardisations and interoperability to business-driven and technologically driven changes for competitive advantages.

2.9 Conclusion

In summarizing this chapter, a systematic review was used to identify previous studies on the impact of BDA for OP based on methodological approach, mediators/moderators used, arguments and findings. The research used a systematic review protocol and a total of 599 papers were screened. Accessibility criteria with inclusion and exclusion strategies was applied, and a total of 48 primary study research were reviewed. Furthermore, concepts of IA and security awareness for agile practices were performed. Gaps and key findings were further discussed, and the study was able to contribute towards literature.

The review provided potential relevance on the utilisation of BDA for OP using EA as a mediating effect and focused on enhancing security awareness to problems associated by adapting to agile practices using secured awareness platform useful in-service request processes of service organisations. Implementing BDA and IA into organisational

Information Technology/Information Systems (IT/IS) structure will improve analytical capabilities for information processing and facilitate intelligent data-driven decision-making. Therefore, reducing uncertainties and enabling agile practices.

Chapter 3: Methodological Approach

3.1 Introduction

This chapter discusses the research methodology and processes involved towards experiments and design development. The research builds on research philosophy and theoretical findings of BDA for organisational performance, and using a positivism paradigm theory describes the critical roles played for the benefits of business processes [95]. The research techniques used helps to answer the research questions "*RQii*", and "*RQiii*" which proves the aim of study which is "*exploiting emerging technologies to create an agile and effective technological platform for change management practices, operational stability, and digital transformation*".

To fulfil the research aim and questions, Figure 3.1 illustrates the methodological approach. The research first develops a research model which is based on previous findings of research, and it discusses the research hypothesis. This gives rise to the research method which includes data collection methods, ethical measurement items, and control variables. A case study during the covid-19 era and its impact on service organisations is mentioned. Concepts used for experimental validation and testing are also discussed extensively. Solutions to experimental validation gives rise to research framework design and development in respect to the case study for intelligent decision making and measuring agility of organisations.

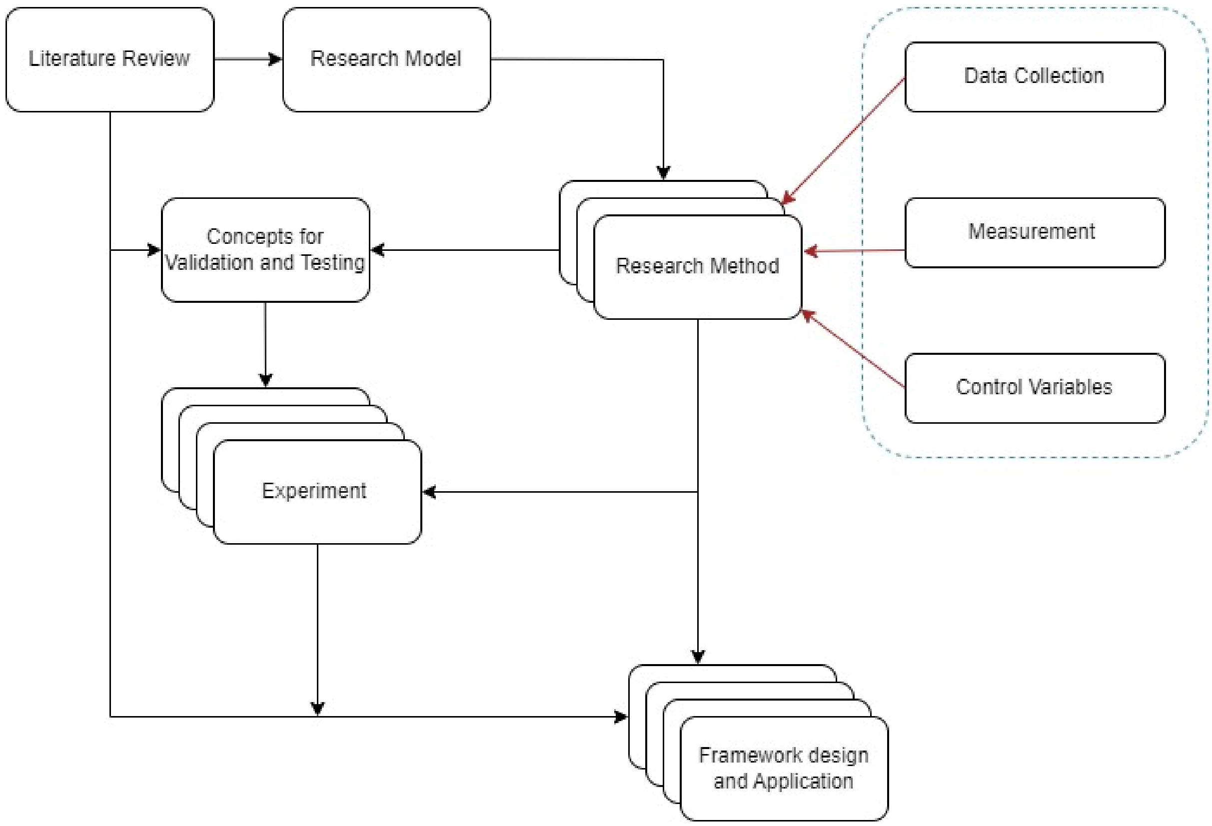


Figure 3. 1 Research Methodology Approach

3.2 Research Philosophy

The research philosophy considers the framework on which this research was conducted using assumptions of knowledge approach and based on guidance of implementations. It helps in understanding the philosophical approach considered for the research by recognizing the research source for nature and knowledge development. According to [96], research philosophy is *a system of beliefs and assumptions based on the development of knowledge* and this is dependent on the research development being carried out regarding a particular field. Before considering the model and approach used in this research, the philosophical assumptions (that is ontology, epistemology, and axiological assumptions) based on objectivism and subjectivism where also considered.

Seeking insights to enhance change management practices of organisations, this research exploited different radical change perspectives based on potentials, conflicts, question domination, contradictions, and deprivations for development.

In developing the research theory approach for the research hypothesis, each research philosophies with regards to computer information systems, business and management research were considered as illustrated in Table 3.1

Table 3. 1 Research philosophy for theory development

Theory	**Ontology**	**Epistemology** (Acceptable knowledge)	**Axiology** (Value roles)	**Research Method**
Positivism	Real, external and independent, granular, ordered	Scientific method, observable and measurable facts, causal explanation, prediction as contributions.	Research is value-free as researcher is neutral and independent. Objective stance maintained.	Deductive, highly structured, quantitative analytical method, a range of data is analysed.
Critical Realism	Stratified or layered, external, intransient, independent, objective structured and causal mechanism	Epistemological relativism, historically situated and transient knowledge, social construction fact, contribution is historically causal explanations.	The research is value-ladened, as there is bias by world views and cultural experiences. There is a trial by researchers to reduce bias and errors.	Reproductive methods, with an in-depth of historically situated analysis of pre-existing structures. Data type method range, fits into the research.
Interpretivism	Socially constructed using cultural language, rich, complex, several meanings, practice, flux of process, experience	Simple concepts and theories with a focus on perspectives, narratives, and stories. Contribution is worldview.	Research is value-bound, subjective and researchers' interpretations are key to research. Research is reflective.	Inductive with small samples and in-depth investigations, qualitative analytical method and a range of data analysed and interpreted.
Postmodernism	Richly structured, nominal, and complex research through power relations, dominated realities, silenced by others, experiences, practices and process flux	Dominant ideologies counted as truth and knowledge that focuses on silences, absences, and oppressed interpretations. Uses power relations of dominant contributions.	Research is value-constituted with research embedded in power relations as research narrative is silently oppressed with researchers being radically relative.	Texts and realities are deconstructed and utilises an in-depth investigation of anomalies. Data types of ranges are usually qualitative analysis methods.
Pragmatism	Quite complex rich and external as reality is practical based on ideas, experiences and flux of processes	Knowledge in specific contexts with true theories that focuses on practical meanings. Theories enable successful actions regarding problem focus and practices for problem solving towards research contributions.	Research is value-driven as it initiates and sustains the researchers doubts and believes based on the reflective nature of the researcher.	A mixed-method analytical approach embedding the combination of qualitative and quantitative analysis methods follows the research problem and questions, with an emphasis on practical solutions.

3.2.1 Philosophical Approach Used

The research philosophy adopted towards hypothetical development was the *positivism* theory. It considered existing theories of previous literatures as well as observable data collection required for analytical testing. Focusing majorly on its objectivity stance, it also focused on what constituted its acceptable knowledge for measurable facts towards its predictive outcomes. Also, as the utilisation of numerical data enhances the use of a positivism theory, it helps in defining functional relationships amongst causal and explanatory factors of independent and dependent variables [97]. Furthermore, it can be ascertained to enhance the internal validity structure of the research design to support causal inference claims. According to [98], the positivist paradigm enables statistical analysis for predictive purposes as it gives more insights to researchers on statistical reliance and generalisation. Therefore, enabling generalisation for development and findings, in comparison to the interpretivist paradigm in which utilises the depth of experiences and perceptions via social context.

We can therefore argue using research theory from [99] that due to its nature of adopting a clear quantitative approach towards investigation, and its clear measurable facts from using predictions as contributions in research, the positivism paradigm view is the most suitable option for the research development.

3.3 Research Model

Following arguments and findings, the relationship amongst BDA and OP using EA as a mediator is considered based on the following hypothesis. Previous research findings indicate technological improvement for EA in business organisations, however, enhancing performances for business operations are demanding [6].

3.3.1 Theoretical Development

Capabilities of BDA are critical to technological growth of business organisations, thus, leading to sustainable competitive advantages in a big data environment [100]. This has attracted tremendous scholarly attention over the years [101] and provided understanding on how organisations processes can adapt to seizing market opportunities, whilst creating business values.

Continuous digitization and business transformation has created several challenges associated with the adaptation of BDA for organisational performance. This includes the lack of technological skills in harnessing value potentials [50] for profitability. Using a resource-based view, it is a necessity for organisations to exploit it strategic and operational capabilities towards adaptation to dynamic environments. Studies show that there is positive effect of BDA and EA on organisational performance [24], and as crucial for investigation on the impacts and influences on business processes. Figure 3.2 illustrates an advanced hypothesized model to be developed for business process adaptation. This is built on existing conceptual model for emergent IT/IS systems [23].

It describes constructs that influences BDA in an organisational system, and this is crucial for managers to understand the data-driven culture of their organisations as well as person skills (comprises of technical and managerial skills) based on Workload for performance influence through adaptation, and competitive advantages.

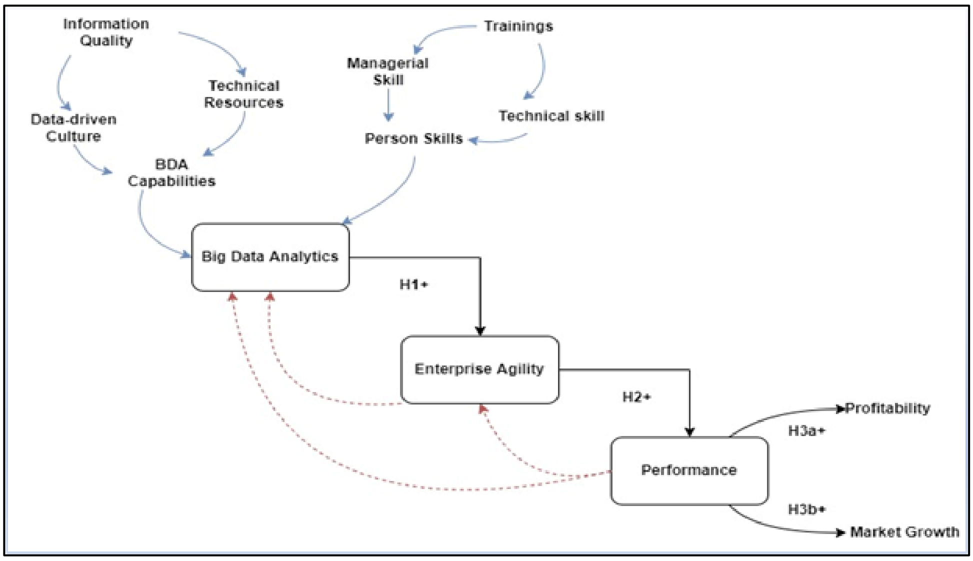


Figure 3. 2 Research Hypothetical Model

3.3.2 Hypothesis Development

The 3-Hypothses define impacts and influences of BDA and EA on organisation performance, based on profitability and market growth. In enabling effective decision making, this helps in determining strategic operability procedures for competitive advantages. Therefore, the following hypothetical views are considered.

i. H1+: BDA influences Enterprise Agility positively.
   Big Data Analytics comprises of several capabilities such as organisational data-driven culture, technical resources, and human skills. It creates possibilities of BDA enabling unpredictable changes due to technological innovation and growth

based on decision-making and human efforts caused by both managerial and technical skills of persons. Although studies have argued that the implementation of agility will enable positive impacts due to swift response to changes for organisational performance [6], [8], [14]. These can be argued that the outcome impact of BDA for EA supports operational and strategic technological innovations. However, agility itself should be used as an intermediate between BDA and organisational performance.

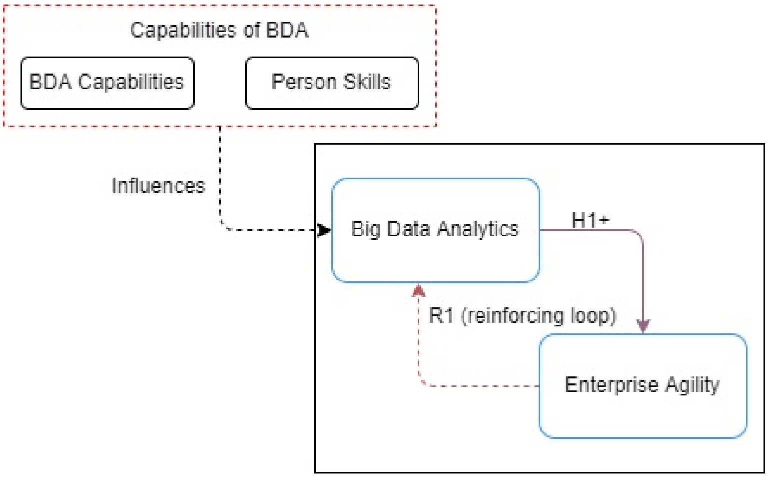


Figure 3. 3 BDA influences EA positively

ii. H2+: An increase in enterprise agility has a positive effect on organisational performance.

Agility responds to uncertainties caused by turbulent technology environments. Research idea encourages organisations in providing better and faster reliable services for competitive markets. A typical example is the Covid-19 pandemic era that affected all businesses and services around the world. This was a pathway for organisations to explore alternative resources of adding values for customers satisfaction, whilst enabling adaptability through response to changes. Therefore, crucial for sensing and responding to turbulent environments, organisations operating in digitally turbulent situations need rapid processes for information systems infrastructure [6]. This can enable agile exploration as an alternative approach towards organisational success. Literature has shown that a greater impact of Information Technology on Enterprise Agility improves sensing and responding capabilities, which was presented by [14], and thus, providing knowledge for data increase of the capability performance. It can be stated that business processes enable optimum performance, as a key requirement to adopt the use of BDA for EA, which enhances competitiveness and data transformation into mindful resourcefulness [102].

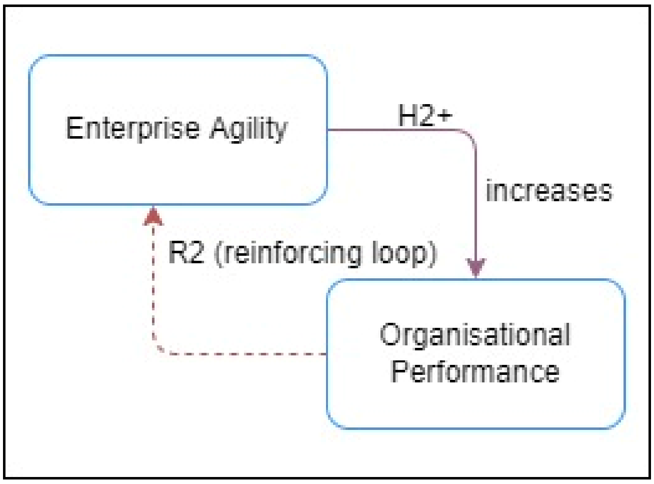


Figure 3. 4 Increase in EA of an organisational system, improves organisational performance

iii. H3a+ and H3b+ An increase in organisational performance, improves profitability, returns and market growth.
Organisational performance can be sub-divided into market profitability, value creation and customers satisfaction. This is vital as it enables growth in both productivity and efficiency of the organisation. It can further be moderated as relationship between consumer satisfaction (comprising of actual customers, potential customers) and customer demands. This is to create an indirect effect that impacts organisational agility, therefore, causing turbulence in target markets.

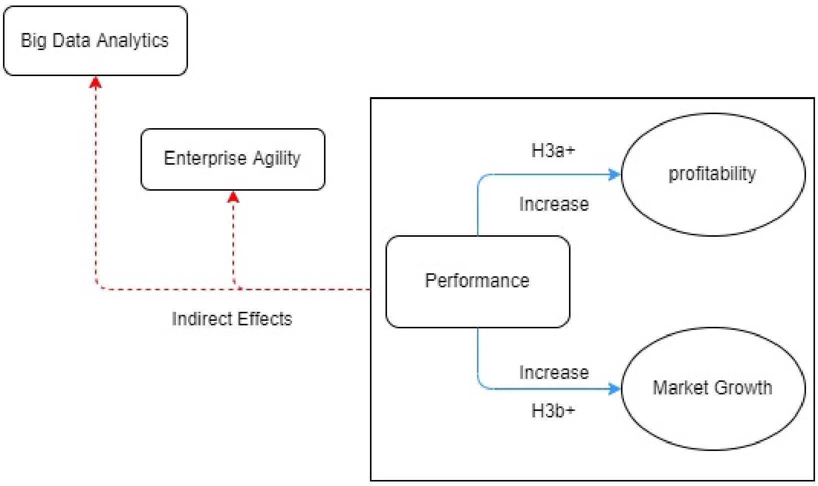


Figure 3. 5 Performance due to profitability for market growth and effects on BDA and EA

3.4 Research Method

In evaluating the 3-hypothesis, survey based on positivism analysis was used in data gathering from an IT service organisation in a developing nation. The method adopted investigated on the relationship between BDA and OP, whilst using EA as a mediator. The sub-sections describe questionnaire, and measures used for the study and for other data analysis.

3.4.1 Instrumentation Development

The designed questionnaires were developed based on previous theoretical basis and hypothetical model to ensure data validity based on content construct. It considered an acceptable error rate of 10% and a 7-point Likert scale was used for measuring all constructs. For content validity and ethical consideration, the non-invasive ethics community at Nottingham Trent University reviewed the questionnaire items and construct. Based on comments given, every request on clarity and items were revised before it was distributed. (Ethical form can be found in the Appendix B of the research).

3.4.2 Data Sample

In sampling data for the research study, service organisations were considered for the research survey and the research was mainly on just primary data.

Surveys are generally questionnaires that could be limited and specific and could be used to measure behaviours, preferences, opinions, behaviour, factual information, and this is all dependent on the predetermined questions [103]. It can also be used to test conceptual modules.

For each research data object, this was considered from service organisations and its motivation was based on incident processes of service organisations. This assists to eliminate time consuming administrative processes as well as reduce human-errors and meantime to recovery errors whilst making service organisational processes more efficient and dependable. Although previous studies state the advent of IA helps towards change management practice, there is need to integrate an intelligent automated system with organisational infrastructural framework for guided autonomous decision making of practitioners by providing then with timely information and help with logical questions [92]. Dynamic organisations will benefit from a digitally transformed IT business service, as key drivers towards IA system adoption involves continuous process and productivity enhancement [94].

3.4.3 Data Collection

The data collection procedure was focused on a target sample of service organisations. Each company was first contacted and then after the acceptance, a formal email was sent to the organisation. The research survey was carried online as, and this consisted of a direct link. The survey consisted of an invitation, purpose of study, participant consent form and 3 sections of survey questions. Data handling was also explained as users can request for a deletion of data in accordance with the GDPR of the United Kingdom.

A total of 126 responses were gathered from 150 questionnaires sent and the data was sampled from service organisations denoted by Company X in a developing economy. Survey's aim was explained in an introductory letter to Company X. Questionnaire for participants knowledge considered specific variable aspect of hypothetical model termed as BDA, agility, and performance measured were based on market growth, profitability, and returns.

3.4.4 Measurement Items

Adapting structural content from [6], each measured content reflected model development with regards to BDA, EA, for OP. All constructs were measured using a 7-point Likert scale and each measure asked models for EA ability and BDA capability.

The entire survey had 42 items and each measured item, was sub-divided into 3-different categories. The first category attributed on professional profile, and enabled understanding of the participants background, emerging technologies, and EA functionalities. The second category investigated organisational culture and values with regards to BDA capabilities, whilst the third section had sub-sections that investigated BDA, agility, and its contribution to performance. Some questions used in the questionnaires were adapted from previous literatures such as [6], [8], [32].

3.5 Case Study

This research used an in-depth case study approach focusing on the "how" phenomenon of research publication presented by [104] and [105]. This is to understand and give answers to specific research question of "*Are the underlying variable model of BDA and EA interrelated; and how can they influence Cs due to productivity and performance in service organisations?*"

3.5.1 The Case Study Approach

In defining the case study approach, the research ensured that an in-depth appreciation of the situation to be solved was related to natural real-life scenario. This is in the context of the change management practices towards the adaptation of unexpected or turbulence situation that are related to changes in environment's and as informed by digital transformation. A paper illustrated on digital transformation and as discussed by [106], it was indicated the need to avoid potential pitfalls that could be encountered in seeking for use case of this nature. Therefore, the research study followed the stake's checklist for assessing quality in defining the case study of the report chosen.

However, due to circumstances of the Covid-19 pandemic, securing access to a particular case-study was difficult due to UK Data Protection Act [107]. On this basis, therefore, it is imperative to have a potential pitfall on case conceptualisation which was later mitigated by developing further knowledge in theoretical and empirical aspect of the literature. As good practice in digital world of communication, an Email approach was chosen and therefore, several emails that were sent followed the research integrity of the NTU and as approved on ethical grounds of the research endeavour. The specific research questionnaires were sent out to different digital service organisations and there are expected potentials in the responses that could have been received and hence, specific focus was determined by only 2- potential responses acknowledged. But this was unexpected as responses could have been more within a specific period of six weeks. In addition, this was traceable to the Data Protection Act 2018 and as demanding during Covid19 to safeguard customers from cyberattacks, to maintain data privacy policies and to avoid breaches of personal data from unauthorised persons.

3.5.2 Case Study Scenario

Company X is an IT solution organisation that concentrates on data analytics for small-medium enterprise in a developing Countries and founded in the year 2005. The company's mission and vision focus on IT service delivery, consultancy, and web service applications, for service development. Company X comprises of over one hundred clients and with 105 projects. The organisation aims to be a reputable company that can withstand other competition, whilst satisfying its customers, and improving its performance based on profitability and thereby providing business solutions. It follows the process of release-approach towards efficient and effective delivery of IT solutions using software applications. Best known for its service delivery on brand identity and web development, the company had to respond to a disruptive environment in the year 2020. This was due to the global Covid-19 pandemic that disrupted its organisational environment and as required for customers' demands on time-to-delivery of services. This also caused staff redundancy and an increased workload from clients, requesting new and updated platforms for stakeholders to enable remote working. With a mission to remain viable and competitive, Company X had to adapt to crucial changes, whilst still being profitable, by optimising cost and integrating agile factors and BDA capabilities into its system. This was based on responding to shift in environment. Although, it is an exceptional perception for the organisation, as trial to explore capabilities for BDA, using agile factors, the company found it difficult to increase its profitability based on its forecasted reviews and as required for decision-making. Company X was faced with other competitive market risk. Therefore, it is important to understand the data analysis presented. This required a specific approach which is based on the relationship of BDA, EA, and Performance towards profitability for improved decision-making, growth, and returns. The research outcomes enabled stability and adaptation to environmental turbulence, caused by market changes and the disruptive technologies.

3.6 Ethical Considerations

The Professional, Social, Ethical and Legal issues relating towards conducting a non-invasive human experiment were considered before distribution of research questionnaires for data gathering. The reason for having an ethical consideration served as a enabling the participants to have all rights to withdraw from the research at any willing point, as well as to ensure data integrity. The research study also ensured confidentiality of personal data of participants as sensitive information was neither collected nor utilised with strict adherence to GDPR compliance.

Before distribution of research survey, the questions had to go through the Nottingham Trent University's non-invasive ethical committee for approval before distribution. The documents submitted for this process included the survey questionnaire and the other following documents as illustrated below:

i. Participant Information Sheet: This provides information about the research project and survey to be considered for the research. It also gives information of different sections within the survey and the terms used for clarification.
ii. Participant Consent Form: The participant consent form is used to show that participants understand the use of their data within the research study.

Following the submission of all documents to the ethical committee, a rejection was first given with feedback for corrections which was resubmitted before an acceptance, and this took about 4 weeks before completion. The participant information sheet and the participant consent form can be found in the Appendix F.

3.7 Structural Equation Modelling (SEM)

Complex causal systems models can be tested using Structural Equation Modelling as it involves multiple interconnected variables.

Structural Equation Modelling (SEM) can be described as *"a powerful statistical analytical method that can be used to examine hypothesized conceptual model and structural relationships at the conceptualization stage, supported by the empirical data due to its sample study."* [108]. Although complicated, it is used to understand infrastructural systems behaviour. SEM is described as a theory-driven and multivariate technique that integrates regression aspects and factor analysis for causal relationship examination and illustrated using path analysis diagrams [109]. It follows the process of hypothetical model development based on theory or previous empirical research, then tests the model against sample data to access and observe the pattern relation. The model can be stated to be of good fit, if it falls within the theoretical principles of SEM and explains the study phenomenon. This research study uses the R Lavaan package for SEM regression implementation as the package aims to answer substantive questions, whilst implementing a new methodological idea.

In performing SEM regression analysis to observe interrelationship amongst variables, some criteria's need to observe and justified to state if a model is of good fit. SEM is composed of 2-models which includes the measurement model and the structural model [110] and this is illustrated in Figure 3.6 below.

i. The measurement model measures latent variables or composite variables whilst,
ii. The structural model is used to test hypothetical dependencies based on its path analysis.

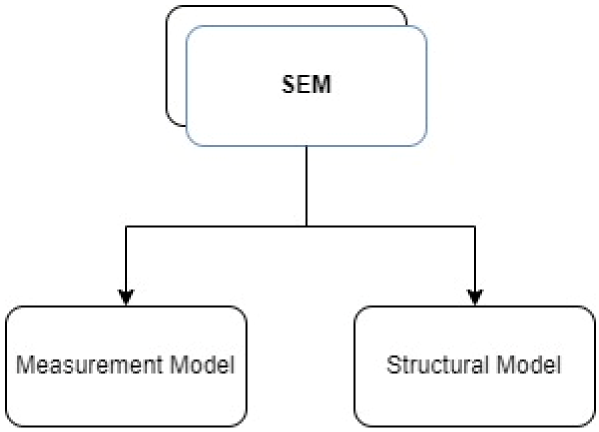


Figure 3. 6 SEM (composed of Measurement and Structural Model)

3.7.1 Observed and Latent Variables

It is necessary to identify the observed and latent variables in the model. The observed variables are variables that exists in the dataset, such that they could be an item, or a manifesting variable and these variables are measured. Latent variables or constructs however, are not in the dataset and can be derived from a factor of other variables, indicating the model's effect or cause [111]. As illustrated in Figure 10, the observed variables are denoted by squares, whilst the latent variables are denoted by circles.

3.7.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis, otherwise known as CFA, is a method used in measuring the latent variables. CFA's commonly *"seeks to confirm if the number of factors (or constructs) and the loadings of observed (indicator) variables on them conform to what is expected on the basis of theory"* [112]. Using latent constructs from other variables, it shares the most variance with other variables and estimates latent variables via correlated variations of the dataset; that is association, and causal relationship. CFA further reduces data dimensions through scale standardisation of multiple indicators for inherent correlations in the datasets [111]. Figure 3.7 below indicates an amplification of the measurement and structural model in CFA as shown in Figure 3.6 above.

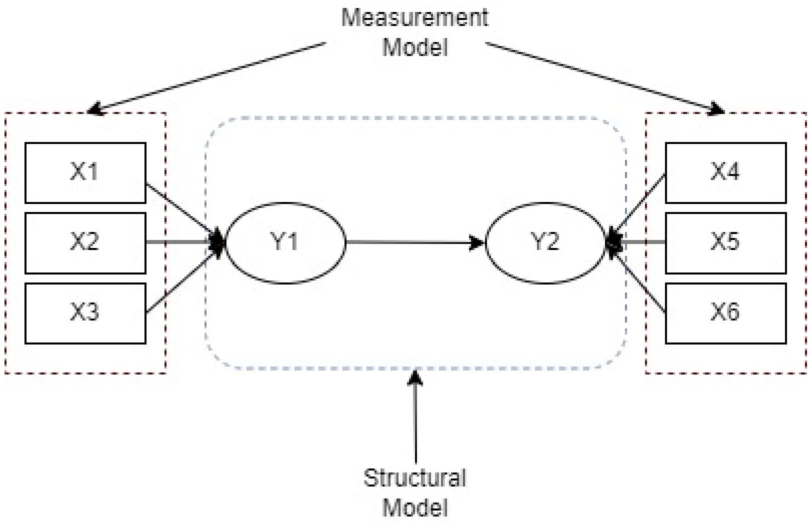


Figure 3. 7 Simple Path Model illustrating the measurement and structural model

In representing constructs by observed variables, a commonly used method to validate and measure the internal consistency and reliability is called Cronbach's Alpha.

A commonly accepted rule in determining the Cronbach's Alpha of a model is as follows:

i. 0 to 0.49 unacceptable
ii. 0.50 to 0.59 poor
iii. 0.60 to 0.69 questionable
iv. 0.70 to 0.79 acceptable
v. 0.80 to 0.89 good
vi. from 0.9 to 1 excellent

The closer Cronbach's Alpha tends to 1.0, the greater its item internal consistency, and this should always be measured before evaluating construct's validity.

3.7.3 Model Evaluation in Structural Equation Modelling (SEM)

When analysing Structural Equation Models (SEM), evaluation is based on test of fit indices to measure each path coefficient (p-values and standard error) and overall model fit (chi-square test and root mean square error of approximation) [111]. If the model fit is satisfied, each individual path can be evaluated. A model is described to be of good fit when the value of the chi-square test is insignificant, one incremental fit index (that is CFI, GFI, TLI, AGFI) and a badness of fit index (which is RMR, RMSEA, SRMR) meet each predetermined criterion. Quantitative indices assist in model evaluation as it calculated the overall goodness of fit and this can be done with any SEM application. There are several model evaluation indices carried out during SEM applications and more fit indices indicate a mis-specified model will be rejected [111]. With some indices having recommended cut-off irrespective of it not been compulsory [113], the following can be calculated during SEM application.

3.7.3.1 Chi-square test (X^2)

The Chi-square text otherwise known as X^2 is a non-parametric test that measures both hypothesis of no association between two or more groups (independence between two variables) and likelihood of observed distribution of data fitting with expected distribution (goodness of fit) [114]. Due to its sensitivity to sample size, it is not comparable amongst several SEMs. X^2 is used to calculate categorical data and this is calculated using the following formular:

$$X^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Where:

O_i = Observed value

E_i = Expected value

3.7.3.2 Comparative Fit Index (CFI)

Comparative Fit Index (CFI) describes the amount of accounted for in a covariance matrix and this ranges from 0.0 to 1.0 [111]; with any value within CFI ≥ 0.95 recognised as a good fit model. It better indicates the model fit as sample size less affects outcomes in comparison to X^2. CFI cam be described to be a fit function specific to a chosen estimation method [115]. In measuring the CFI, its incremental measure is directly based on the non-centrality measure.

Suppose: d = X^2 - df

Where:

df = degrees of freedom of the model

$$CFI = \frac{d\ (Null\ Model) - d(Proposed\ Model)}{d(Null\ Model)}$$

3.7.3.3 (Adjusted) Goodness of Fit Index (GFI/AGFI)

The Goodness of Fit Index (GFI) was proposed in 1982 by [116] and it is the measure of discrepancy between sample covariance matrix (S) and the estimated covariance matrix (∑ ^) [117]. In simpler terms, it is the variance proportion which is accounted for by the estimated population covariance. The value of GFI increases with the addition of more parameters and it can be used to also determine how better a proposed model fits in comparison to a null model. However, the Adjusted Goodness of Fit Index (AGFI) was formulated to resolve the problem of GFI increase due more parameters. The GFI/AGFI is analogous to R^2 and should be greater than .95 and .90, respectively [118].

The algebraic expression for GFI and AGFI is given as:

$$GFI = 1 - \frac{tr(\sum^{-1} S - I)^2}{tr(\sum^{-1} S)}$$

$$AGFI = 1 - \frac{k(k+1)}{2df_{test}} (1 - GFI)$$

Where:

S = Sample covariance matrix,	df_{test} = degree of test model
∑ = Estimated covariance matrix,	k = number of observed variables
tr = trace of a matrix,	*I = identity matrix*

It is also important to note that GFI has a positive relationship between the sample size.

3.7.3.4 Root Mean Square Error of Approximation (RMSEA)

Root Mean Square Error of Approximation (RMSEA) gives relevant information on the badness of fit such that lower values of RMSEA indicates the model is of good fit [119]. It is described to show better fit for models with a much larger degree of freedom. In RMSEA index, a 0 indicates perfect model fit in comparison to larger values. This is useful for model detection misspecification and outcomes are not affected by sample size when compared to X^2 [111]. RMSEA is also known as the absolute measure of fit because, it is based on non-centrality parameter. For models with a small degree of freedom (*df*) and low sample size (N), the value of RMSEA could artificially have a large value of RMSEA. Therefore, [120] state that RMSEA values should not be computed (although possible) for low “*df*” models. A rule of thumb for confidence interval states RMSEA values should not be worse than 0.05 and its upper value is not very large at 0.08.

Computational formular in calculating RMSEA is given below and if X^2 < *df,* RMSEA is set to zero.

$$RMSEA = \frac{\sqrt{(X^2 - df)}}{\sqrt{[df(N-1)]}}$$

Where:

N = Sample size,

df = degree of freedom

3.7.3.5 Standardized Root Mean Square Residual (SRMR)

Standardized Root Mean Square Residual (SRMR) it an absolute measure of fit and it is the difference between observed correlation and predictive correlation. For perfect fits in SRMR, a value of zero signifies this. When it comes to the complexity of the model, there is no penalty for SRMR as a value less than .08 is considered as a good fit.

In summary, evaluating models in SEM have certain criteria’s, (as shown in Table 3.2) which should be followed as the fit refers to the ability of data reproduction. Although academics still argue on these given criteria’s and what is meant by “*reasonably data consistent*”, it is critical to understand that a good fitting model can be produced irrespective of specification error.

Table 3. 2 Reference summary for SEM adjustment indices

Model Evaluation	Very Good	Good	Fair	Bad
X^2 /*df*	≤ 1	) 1,2}	) 2, 5]	> 5
CFI	≥ 0.95	[0.95, 0.85(	)0.8, 0.85[	<0.8
RMSEA	≤ 0.05	] 0.05, 0.08]	]0.08, 0.1]	> 1.0

3.8 Summary

To summarize this chapter, the research approach in which this research was carried out has been mentioned. It has also discussed theoretical approach based on developing the research hypothesis for experimental investigation. Furthermore, the chosen method for data gathering and sample has been explained extensively and this is based on positivism paradigm due to business process benefits. Following the methodological approach, measurement items have further been elaborated and the case study of the research focus has been discussed.

This chapter has also described the analytical techniques used for experimental analysis which is Structural Equation Modelling (SEM). Although it is still argued amongst academics on reference criterion for indices adjustment for model fitness, it has been able to explain evaluation concepts, formulars, and suggest what is required for a model to be considered of good fit. Each evaluation technique and research approach described within this chapter will be encountered throughout this thesis. This includes tools for experimental analysis and steps to be achieved towards realizing the research outcomes.

Chapter 4: Big Data Analytics and Enterprise Agility for Customer Satisfaction: A Structural Equation Modelling approach on Variable Interrelationship

4.1 Introduction

Technological disruptions caused by digital transformation has continued to destabilise organisational business processes, and organisations are faced with events of restructuring its business culture towards optimising customers experience and remaining competitive. In doing so, they need to be agile in responding to changes whilst capitalising on using Big Data for emerging technologies such as Artificial Intelligent (AI) for Machine Learning (ML), Natural Language Processing (NLP) for Intelligent Automation (IA). This aids valuable insights towards decision-making for intelligent business processes [121]. This chapter explores experimentally, the interrelationship amongst BDA and EA for Cs based on OP for profitability and market growth based on the hypothesis (H1), (H2) and (H3a+ and H3b+). It also investigates hypothesis for new metrics development given that a common theme with regards to ET approach is sustained. As mentioned previously in chapter 1, results of quantitative analysis, data analysis and path coefficient illustrations using SEM approach are presented within this chapter. Scientific contributions of the experimental outcomes are presented where appropriable.

4.2 Understanding Big Data Analytics (BDA) and Enterprise Agility (EA) for Customer Satisfaction (Cs) based on Organisational Performance (OP)

The integration of Big Data Analytics (BDA) and Enterprise Agility (EA) for Customer Satisfaction (Cs) based on performance will aid business applications for data analysis towards an effective enterprise. This can be useful for understanding business for Strategic Business Factors (SBF), therefore aiding Market Product Competition (MPC) for effective customer satisfaction and decision making. Grounded upon previous research by [6], the experimental analysis in this research aids to use SEM as a specific analytical approach in understanding the interrelationship between all considered variables which are BDA, EA, OP and Cs. The analytical results therefore pave way for application development using IA and SOAR for organisational development in dynamic response to EA.

Furthermore, research work of [29], has also called for the integration and investigation amongst BDA, agility, ambidexterity and performance as it indicated each variables acted as key driving forces for an efficient business process, leading to faster response to dynamic changes. It is therefore necessary to understand each specific variable process based on its several constructs to improve organisation performance for profitability and market growth aiding better Customers satisfactions (Cs).

4.3 Data Analysis on Survey

Survey data analysis draws conclusion on data gathered, by turning it into insights and answers to help improve and respond to academic research questions whilst providing contributions for professionals in the industry. In carrying out data analysis, descriptive analysis was done based on research demographics and SEM analysis using RStudio to access the measurement model and structural model based to validate the develop hypothesis.

4.3.1 Survey Questions

The survey questions used in this research and as illustrated in Appendix E1 were split into three (3) sections labelled Section 1, Section 2 and Section 3 respectively.

i. Section 1 consisted of the persons professional profile, therefore, making up the research demographics in respect to job roles, age range, and educational qualifications. Other research demographic aspects such as gender, race, and income level were omitted purposely to improve participant's confidentiality in accordance to the Data Protection Act 2018 [107] of the UK's GDPR implementation.
ii. Section 2 questioned Organizational values and Culture, and this section was designed to understand knowledge-based approach within the organisation (both technical and organisational). The section was also designed to understand the required effort put in by the organisation towards the development of persons and values for Big Data Analytics in turbulent environments.
iii. Section 3 within the survey questionnaire, was designed to analyse the relationship amongst the considered variables within the research model. It

focused on BDA and EA and their contribution towards organisational performance for effective profitability due to customer's satisfaction and market growth. It investigated capability measures of the organisation due to BDA, measurement of EA within the organisation focusing on both market and technological turbulence and OP increment and decrement within the last 2 years.

Some questions used in the research were sampled from previous literature such as [6], [32], [75] and the utilisation of a 7-point Likert scale was due to its sensitivity for accurate evaluation of interfaces, for improvement due to the philosophical approach. The research questions as measured on the 7-point Likert scale can be found in Appendix E1.

4.3.2 Research Demographics

As mentioned (in section 3.3.3) above, the study used a survey questionnaire and data was gathered from 126 participants which included managers, assistant managers, supervisors, specialists, researchers, engineers, technical support engineers etc. as indicated in Table 4.1 below from IT service organisations. This is because this group of respondents were better positioned in knowledge of ET trends and organisational behaviour and culture with regards to satisfying customers for performance purposes, thereby improving profitability and organisational growth.

Table 4. 1 Job roles of participants

Job Type	Percentage
Technical support engineer	27.42%
Manager	13.71%
Assistant Manager	9.68%
Technical Support Supervisor	7.26%
Product Manager	6.45%
Research Engineer	5.65%
Creative Director	4.84%
Senior Application Developer	4.03%
Maintenance Engineer	4.03%
IT Consultant	3.23%
Client Service Manager	2.42%
Field Service Engineer	2.42%
IT Entrepreneur	2.42%
IT Secretary	1.61%
Admin Officer	1.61%
Senior Commercial officer	1.61%
IT Apprentice	0.81%
Blank	0.81%
Grand Total	100.00%

Based on the graphical illustration of Figure 4 .1, it can be illustrated that 27.42% of the participants worked within the technical support engineering role, to whom are the first point of response to the customers to enable a service level agreement are met with regards to the organisational policy.

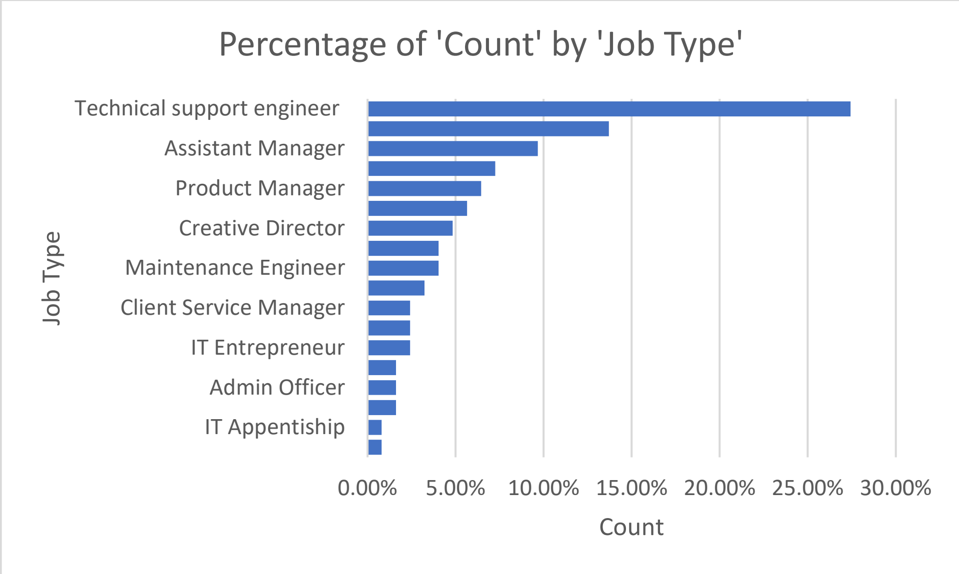


Figure 4. 1 Graphical illustration of participants response

Table 4.2 also illustrates the response rate based on age of persons in the organisation. It can be noticed that majority of respondents working within IT service organisational industries are within the ages of 36 – 45 and this accounts for 46.4% of persons which equates to almost half of the responses as well as the ages of 26 -35 coming in next with a percentage of 31.2%. Therefore, this clearly states that most respondents are within the working-class ages.

Table 4. 2 Age rate response

Row Labels	Count
18 - 25	15
26 - 35	39
36 - 45	58
46 - 55	13
Grand Total	125

Furthermore, in getting more clarity and insights for experimental analysis, educational status was considered as it provides a diverse range of social outcomes for operationalisation [122]. Reviewing Table 4.3, it can be noted that only 3-respondents had a doctorate degree, whilst master's degree holders and bachelor's degree holders had a responsive rate of 66 and 43 respectively.

Table 4. 3 Educational background of respondents

Education	Respondents
Masters	66
Bachelor's	43
College Graduate	5
PGD	3
Doctorate	3
A-Levels	2
Law degree	2
(blank)	
Grand Total	124

4.3.3 Results of Measurement Model Validation

Evaluating the model measurement for validation, the first step performed was to assure the internal consistency of constructs via Confirmatory Factory Analysis (CFA). In doing so, data gathered was checked against the Multivariate Normality (MVN) assumption, using the Mardia's test of multivariate analysis. The results achieved as indicated in Table 4.4 below showed that MVN result is "*NO*", therefore, denoting that the data gathered deviates from a multivariate normal distribution significantly, and results of chi-square text (X^2) and pathway significance test may be unreliable.

Table 4. 4 Mardia's test of multivariate analysis

	Test	Statistics	p Value	Result
## 1	Mardia Skewness	12764.7316066101	3.15764412256578e-42	NO
## 2	Mardia Kurtosis	6.67074320152454	2.54511967057169e-11	NO
## 3	MVN	<NA>	<NA>	NO

To eliminate this problem for a good analytical result of X^2 and pathway significance test for reliable estimates, the research study therefore applied the concept of bootstrapping [109] in all its analytical stages.

The CFA was performed with the R studio application using the Lavaan 0.6 - 15 comprehensive package for SEM. To specify the measurement model, the experiment considered all operators of the Lavaan package for identifying relationships amongst variables. Table 4.5 illustrates all operators in the Lavaan package, however, the considered set based on the formulars used during the research experiment includes the latent variable, regression, and co-variance.

Table 4. 5 Lavaan Operators

Formular	Operator	Mnemonic
Latent Variable	$= \sim$	Manifested by
Regression	$\sim$	Regressed on
Co-Variance	$\sim\sim$	Correlated with
Intercept	$1 \sim$	Intercept on

In verifying the operationalisation and measurement of the latent variables, the research hypothesis explained in section 3.2.2 and illustrated in Figure 3.2, was detailed following the hypothetical measurement model, and fitted to the survey data. Each item considered was identified as the latent construct and due to the violation of multivariate normality assumption (MVN), the bootstrapping estimator option was used. The equation below exemplifies the hypothetical measurement model. Bootstrapping estimator for generating a bias-corrected parameter estimate for all path coefficients in the model was set to a random bootstrap option of 2000. This was to ensure that a bootstrap-corrected p value for the chi-square test of model fit was computed accurately.

$$BDA = \sim data_{volume} + bdaTools_{measure} + value_{creation} + product_{optimise}$$

$$EA = \sim \mathrm{customer}_{\mathrm{demand}} + \mathrm{newTech}_{\mathrm{adapt}} + \mathrm{quality}_{\mathrm{improvement}} + \mathrm{regPrice}_{\mathrm{review}}$$

$$PF = \sim \mathrm{proft} + \mathrm{market}_{\mathrm{growth}} + \mathrm{returns}$$

$$CS = \sim \mathrm{cust}_{\mathrm{feedback}} + \mathrm{prod}_{\mathrm{recommend}} + \mathrm{quality}_{\mathrm{improvement}}$$

4.3.3.1 Confirmatory Factor Analysis (CFA) Results

Following the specified hypothetical model measurement, and as described in the given equation above, the results gained is based using our data as arguments for the theoretical model. The Lavaan CFA function *"i.e., CFA ()"* was called from its comprehensive package to fit the model into the data as shown in the Appendix C. Using the bootstrap test option once again of 2000 random sample iterations, the result of the CFA is given in Table 4.6 below.

Table 4. 6 Confirmatory Factor Analysis (CFA) Model Fit

CFA_model_fit				
##	lavaan 0.6.15 ended normally after 63 iterations			
##	Estimator	ML		
##	Optimization method	NLMINB		
##	Number of model parameters	33		
##			Used	Total
##	Number of observations		118	125
##				
##	Model Test User Model:			
##				
##	Test statistic	155.387		
##	Degrees of freedom	58		
##	P-value (Chi-square)	0.000		
##	P-value (Bollen-Stine bootstrap)	0.001		

Converging normally after 63 iterations made, the output includes an estimator which in the case of this research a Maximum Likelihood was used for maximizing the probability of obtaining the observed data. Also, degree of freedom was observed as 58 as it measured the number of independent varying values. From the output results, 2 P-values are denoted with as 0.000 for chi-square and 0.001 for the bootstrapping. The reason for having both 2-P-values is due to multivariate normality assumption as discussed in section 4.3.2 above. Exploring the results of the P-value and comparing it for statistical significance, the bootstrap p-value exceeded threshold by being insignificant for positive results. Therefore, it indicates the model fit is positive as a major difference between both the observed variables and hypothetical model amongst each data variable can be declared as statistically negligible.

4.3.3.2 Goodness of Fit Index Evaluation

The Goodness of Fit Index (GFI) is compared against recommended value cut-off for evaluation and validation of a satisfactory model fit. This process gives explanations and answers to the research question 2 (*RQii*), which is "*Are the underlying variable model of*

Big Data Analytics (BDA) and Enterprise Agility (EA) interrelated; and how can they influence Customer's Satisfaction (Cs) due to productivity and performance in service organisations?"

Table 4. 7 Hypothetical Model Goodness of Fit Index (GFI)

fitMeasures (CFA_model_fit, c("cfi", "gfi", "agfi", "rmsea"))				
##	cfi	gfi	agfi	rmsea
##	0.885	0.846	0.758	0.119

The table above indicates the results achieved for Confirmatory Factor Analysis (CFA). Based on the SEM code to obtain the common indices, each value meets its recommended cut-off, therefore indicating that the proposed hypothetical model gives a significant explanation. This means that the underlying variables observed in the model data are inter-related.

4.3.3.3 Model Regression Pathway

Based on the model evaluation and the goodness of fit indicating the model is of good fit, the research therefore investigates the causal relationship amongst each model variables. In returning standard estimates, the Lavaan function standardized solutions () was called. Based on our results as illustrated in Table 4.8 below, the variances obtained based on estimated values and its standard errors. All fit measures as indicated in the appendices are greater than the threshold value of 0.5 except quality improvement for EA. Therefore, this indicates that quality improvement should not be a measure for EA processes of organisations. The resulting standard error falls within a tight range value of ±30%, indicating the discrepancy expected within the sampled estimate and this is based on the sample size used. It also indicates that the estimated values are exactly or close enough to the true values, whilst the p-values indicate that the model is statistically significant with a good fit.

Table 4. 8 Result of Model Variance

Variances:

##		Estimate	Std. Error	z-value	P(> |z|)	Std.lv	Std.all
##	BDA	1.180	0.349	3.385	0.001	1.000	1.000
##	.EA	0.333	0.119	2.798	0.005	0.421	0.421
##	.PF	0.466	0.139	3.198	0.001	0.493	0.493
##	.CS	0.729	0.193	3.782	0.000	0.614	0.614

The regressive pathways are synthesized in Figure 4.2, and it specifies the structural model of the research design. Each pathway is clearly defined based on variables and their dependencies. A linear relationship is assumed between each variable indicator, and this is seen between BDA and EA, PF and EA as well as PF and CS and as illustrated in the appendices for regressions. Although this does not clearly explain an out of sample prediction, it can be used to illustrate and predict the output of new value cases, when measuring organisational agility based on customers satisfaction due to performance for market growth and productivity level of organisations. This research can conclude that the predictions made with regards to the hypothetical views are based on a reflective structural equative model and further works should consider using a Partial Least Square approach, although results that can be gathered from this approach may not be completely factual.

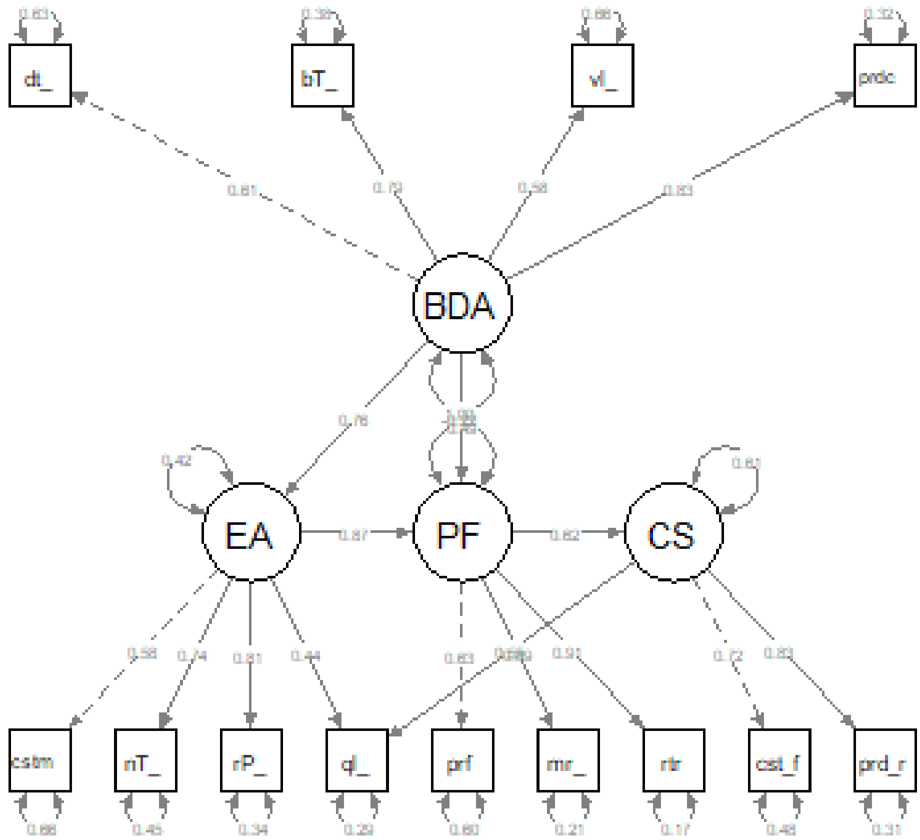


Figure 4. 2 Regressive pathway based on "what = paths", "whatLabels = Stand" and "rotation =1"

4.4 Chapter Summary

In concluding this research chapter, the raw data used a multivariate normal distribution for validating the model and addressed the research question of interrelationship amongst variables in the model and hypothetical design. This was done by calculating the fit measures based on average values of CFI, SRMR, RMSEA with accompanying calculations of AGFI, NFI and GFI for each simulation conditions and values deduced were "gfi = 0.820", "agfi = 0.726", "nfi = 0.791", "cfi = 0.842", "rmsea = 0.137" and "srmr = 0.130". These values follow cut off in Table 3.2 referenced above and [123].

Furthermore, using the SEM approach has managed the complex situation of models and offered promising cognitive framework in nuanced understanding of analyzing the impacts of "BDA" and "EA" for Cs due to performance and productivity in organizations. This has also given rise to developing an improved system capability for intelligent decision making based on agile approaches to managing complex environments caused by emerging technological disruption.

Chapter 5: New Idea of Emerging Technology: Intelligent Automation (IA) and Agile Processes for the Application Development and for Intelligent Decision-Making

5.1 Introduction

To improve business adaptation using agile response based on turbulent technological environments, digital transformation permits the process of organisations to either modify or create new strategic business models. It is therefore necessary to implement a platform via the combination of human skills and information systems infrastructure in responding to change dynamics. Intelligent Automation (IA) helps in improving system infrastructure with regards to human behaviour [76]. This is useful to exploit different practices of virtualization to accomplish human tasks [5]. Outcomes results to enhance and improve intelligent decision making, service processes can involve the integration of Robotic Process Automation (RPA) and Artificial Intelligence (AI). These are based on technological capabilities and automation for business service processes.

This chapter provides new insights for adoption into business processes as it explores how to integrate IA into organisation's infrastructure for agility enhancement. It further designs and develops a dashboard application, based on an IA framework approach in service organisations. This can promote competitive advantages and for organisation performance purposes. Research contribution in this chapter improves infrastructural system capability for intelligent decision making via agile approaches. It helps in handling complex turbulent environment based on understanding of EA level within the system. Also, cyber security awareness requirements are based on incidents and policies to prevent redundancies caused by human errors.

5.2 Intelligent Automation (IA) and Enterprise Agility (EA): A Web Application for Agility Assessment and Service Management

The utilisation of Big Data Analytics (BDA) enables organisations to remain in competitive markets as it enhances a data-driven and decision-making cultures. However, dynamic operational environments can be quite complicated as it remains competitive leading to continuous fluctuation. As digital transformation encourages the use of Robotic Process Automation (RPA), for example, in dynamic business environment, there is continuous improvement of information systems infrastructure that requires automation of human behaviour [76]. This process is demanding for performance optimisation. Therefore, this brings about adaptation of RPA on Business Process Management (BPM) and with the use of AI to emulate humans [124] using an intelligent software.

IA integrates RPA and AI [79] are designed for technological capabilities, but organisation can explore the usefulness through technological readiness and process automations of business process applications. However, this process can mimic business process tasks and as demanding to improve enterprise agility. The usage of these application in predictive situation can influence process insights, which are good for accurate decision making, whilst, increasing organisational scalability to meet customers' demands and for customer satisfaction.

The novelty of this study is designing and implementing a web application based on framework principles of IA and aimed at calculating enterprise agility of service organisations. The application also facilitates service request management, feedback collection, and provides modelling and analysis capabilities. Outcomes is to enable service organisations assess their agility levels, improve service request delivery, and make intelligent data-driven decisions to enhance their overall performance.

5.3 System Design and Framework Architecture

The system design and framework architecture play a crucial role in the web application. The system design gives insight on the overall structure and interaction within the web application. IA impacts organisational operations such that systems with IA are capable of automating business processes repetitively on the go. This creates a reliable process for effective decision making.

5.3.1 System Design and Architecture

The software application was designed using Oracle APEX. This is a low code application that offers the ability to create reports, charts and pages which could be used in data reviews and manipulation [125]. Residing within the oracle database with regards to its schematics, the system architecture consists of 3-different layers which is known as the browser, mid-tier and database tier and it is illustrated in the Figure 5.1.

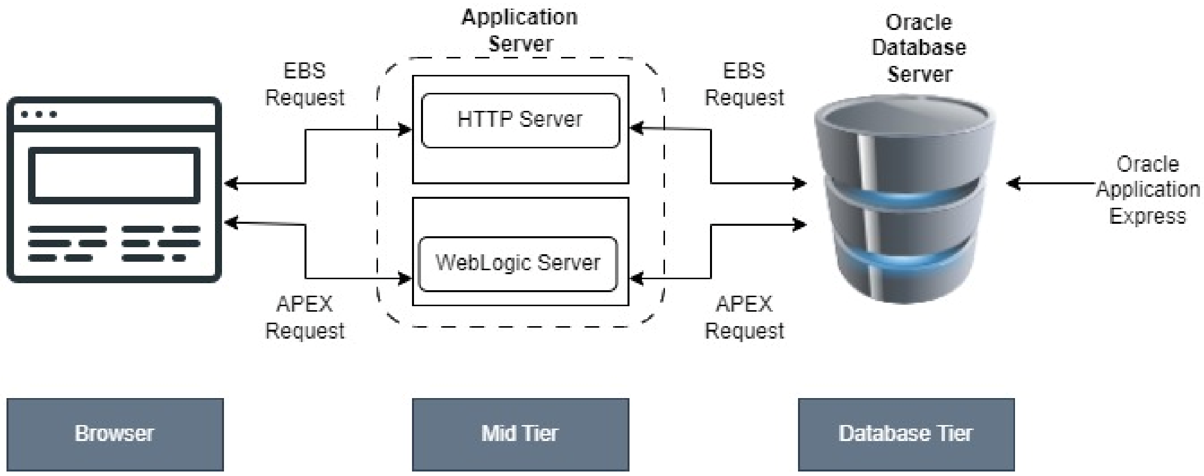


Figure 5. 1 Oracle APEX Web Architecture

i. The *Browser* is the user interface of the web application the enables communication between each layer.

ii. The *Mid-Tier* utilises Oracle Rest Data Services (ORDS). ORDS is a java-based solution that is certified with oracle WebLogic servers, Jetty servers and Apache tomcat.

iii. The Oracle database server is recommended for configuring Oracle APEX which is used in developing the web application. Each APEX workspace is defined within the E-business suite database objects.

5.3.2 User Interface Design

In creating the system design, the user interface assists in depicting the interaction between the system users and the web application. It also provides a vital information via contribution for user experience as the web application needs to be easy to use. Figure 5.2 below depicts an interactive flow of the web application. The user-interface further considers usability, accessibility, and responsiveness across several devices of different sizes. Working with Oracle APEX enables rendering of the application on different devices as it enables a browser-based interface for productivity flexibility and ease of use [125].

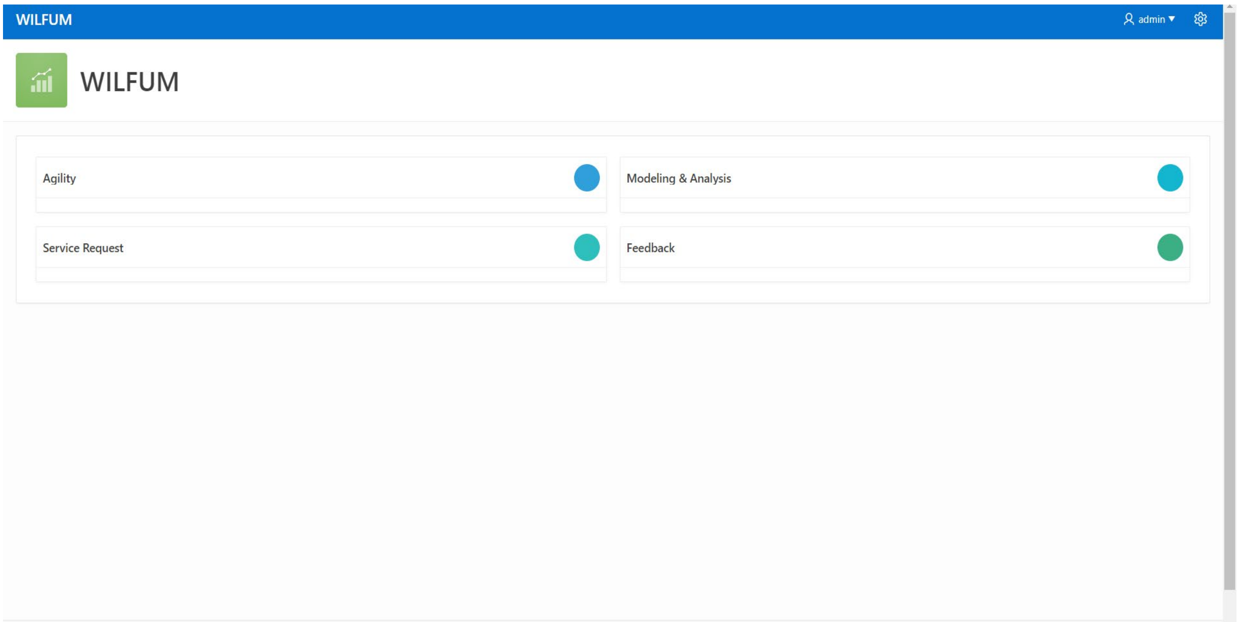


Figure 5. 2 Web Application User Interface of Dashboard Application

In Figure 5.2, it shows the Dashboard application considered for a standard user. Each user can click on the item of choice for viewing and performing simple task required within the application.

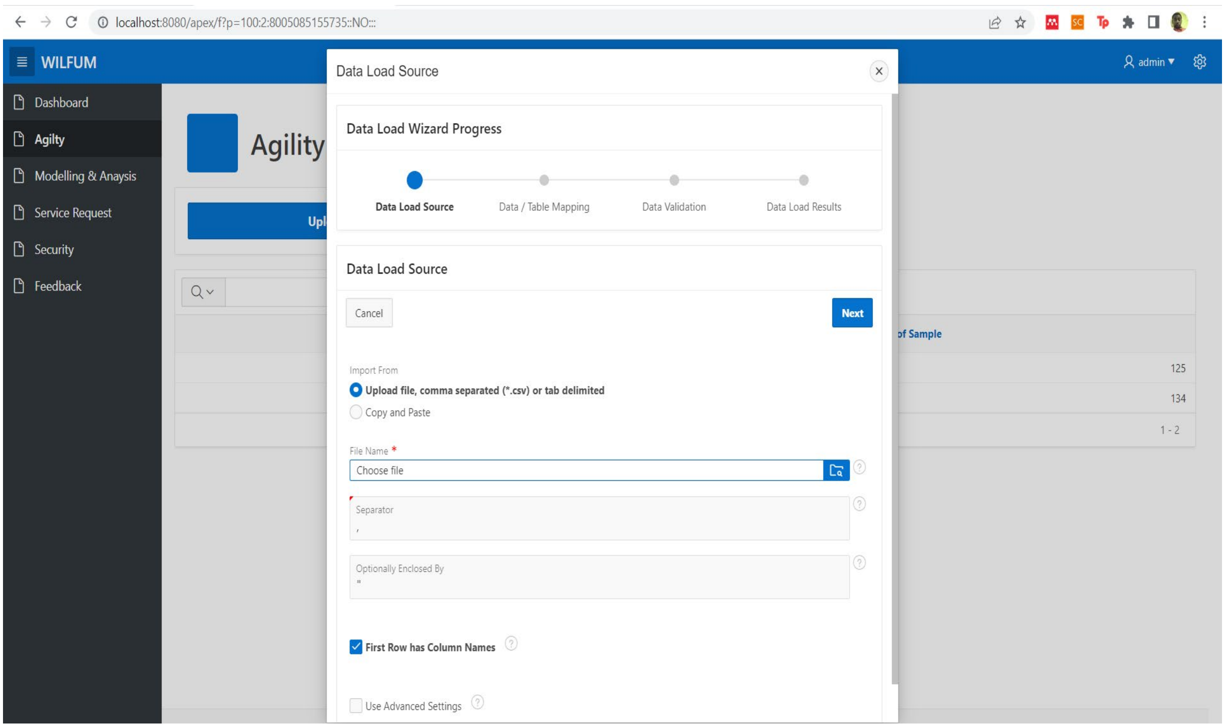


Figure 5. 3 User Interface of Web Application Displaying Ease of Functionality

Figure 5.3 illustrated, depicts easy of functionality for accessing a functionality of the user interface with understandable qualities and aesthetics that enables fast learning.

5.3.3 Technology Stack Selection

Defining the technological stack for the web application was quite easy as this is predefined in Oracle APEX. Technology stack encompasses libraries, frameworks, programming languages and tools used in developing the application. Security and application performance were also considered for project alignment based on Intelligent Automation and for adaptive response to change management principles.

The web application used the Oracle RAD stack, and this is based on 3-major components which includes:

i. The Oracle REST Data Services (ORDS),
ii. ii. Oracle APEX, and
iii. iii. The Oracle Database.

With no features cost, working with the oracle database entailed all stack features were acquired. The image below illustrates the technological stack used in the application.

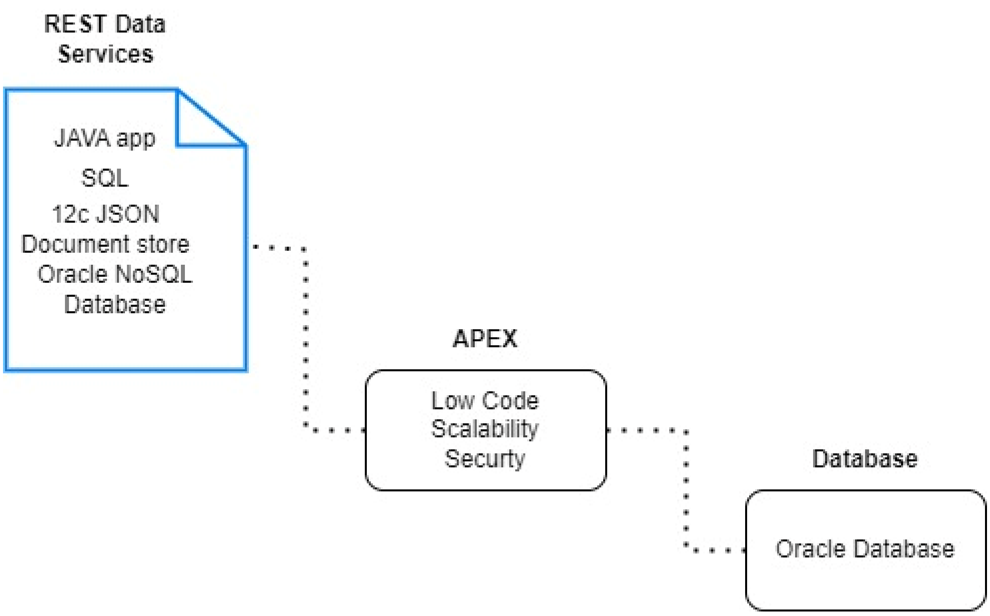


Figure 5. 4 Technology Stack Selection for Web Application Development

5.4 Cyber Security for Intelligent Automation (IA) and Enterprise Agility (EA)

Using Intelligent Automation (IA) and Enterprise Agility (EA) for organisation performances will require the need for cyber security initiatives as applied to the user input logs on the Dashboard of the research designed. Security awareness usually occurs within service request as indicated in the high-level diagram of Figure 5.5 below. This is due to activities caused by cyber vulnerabilities and false positives. It is extremely vital to any log event of cybercrimes either false or true. Therefore, making it necessary to understand the alert system process for incident response of service organisations. thereby creating an agile effect of change management practices.

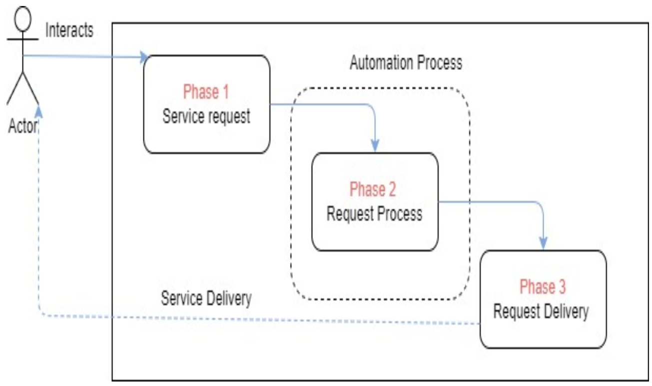


Figure 5. 5 High-Level Service request Process

Illustrating a step-by-step process of the diagram above can be indicated in Figure 5.6. The Oracle APEX application, enables log collections based on incident responses and this can only be accessed fully by the application's admin. Furthermore, for organisational agility to be fully competent, it should be able to respond rapidly to security threats (either true positives or false positives), therefore preventing redundancy and vulnerability. The Incident Access Process (IAP) as illustrated below encourages organisational service systems to be efficient and dependable. It also integrates the Security Orchestration Automation Response platform which when deployed, and integrates security tools and runs sets of tasks based on unification, orchestration, and automation [88]. When sending an application error via the IAP, the application validates this error based on false positive or if it is a proper alert. If it is a false positive, the error log report updates with a "- ", for the user, indicating it is not a true error. However, if positive, it validates and evaluates the error and then executes a response directly (via delivery) to the user after logging the error for administrative purposes. The delivery of the error is via a message, and it could either be that the error caused by login credentials which was authenticated, or it must deal with the application itself.

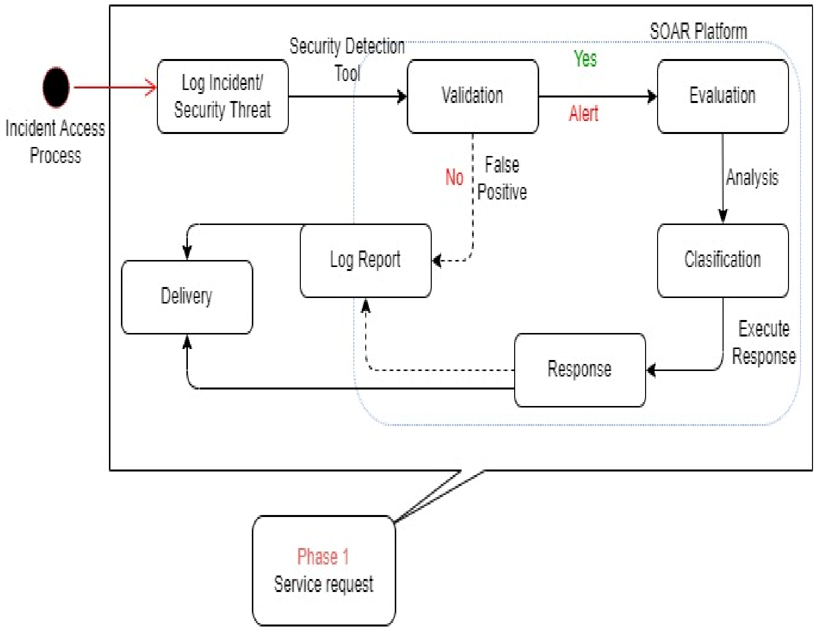
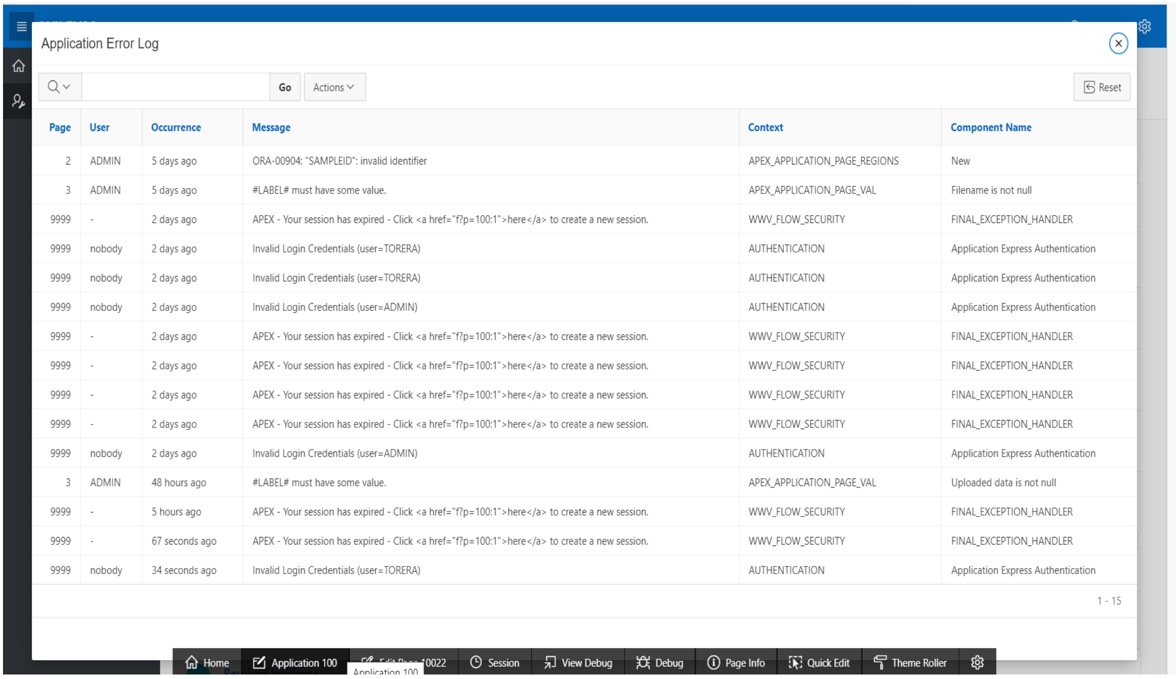


Figure 5. 6 Security Awareness based on Incident Response Process in Service Organisations

For every error recorded, a message is passed onto the admin and the context of the error is given following automated processes of the SOAR platform as illustrated above. The application error log is depicted in Figure 5.7 which shows the administrator every error that has occurred within the system, its occurrence, the message of the error and its context.



Application Error Log

Page	User	Occurrence	Message	Context	Component Name
2	ADMIN	5 days ago	ORA-00904: "SAMPLEID": invalid identifier	APEX_APPLICATION_PAGE_REGIONS	New
3	ADMIN	5 days ago	#LABEL# must have some value.	APEX_APPLICATION_PAGE_VAL	Filename is not null
9999	-	2 days ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	nobody	2 days ago	Invalid Login Credentials (user=TORERA)	AUTHENTICATION	Application Express Authentication
9999	nobody	2 days ago	Invalid Login Credentials (user=TORERA)	AUTHENTICATION	Application Express Authentication
9999	nobody	2 days ago	Invalid Login Credentials (user=ADMIN)	AUTHENTICATION	Application Express Authentication
9999	-	2 days ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	-	2 days ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	-	2 days ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	-	2 days ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	nobody	2 days ago	Invalid Login Credentials (user=ADMIN)	AUTHENTICATION	Application Express Authentication
3	ADMIN	48 hours ago	#LABEL# must have some value.	APEX_APPLICATION_PAGE_VAL	Uploaded data is not null
9999	-	5 hours ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	-	67 seconds ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	nobody	34 seconds ago	Invalid Login Credentials (user=TORERA)	AUTHENTICATION	Application Express Authentication

1 - 15

Figure 5. 7 Application Error Logs for Cyber Security purposes

5.5 Framework for Intelligent Automated System

The exploitation of Intelligent Automation (IA) as an emerging technological change concept for business systems, enables a high impact process for service organisations. This requires strategic and operational direction through linked value drivers [126].

In designing a conceptual framework for service request based on IA platforms, it is quite crucial to consider the actors/users. IA occurs within business process infrastructures to improve Mean-Time-To-Respond (MTTR) rates based on digital services. Following service incident requests in service organisations, it further prompts IT users and managements on tasks to be performed such that it identifies opportunities and prioritise request purposes. Consisting of 3 main phases, the service requests based on incident response can be broken down into:

i. the request phase,
ii. the automated phase, and
iii. the delivery phase.

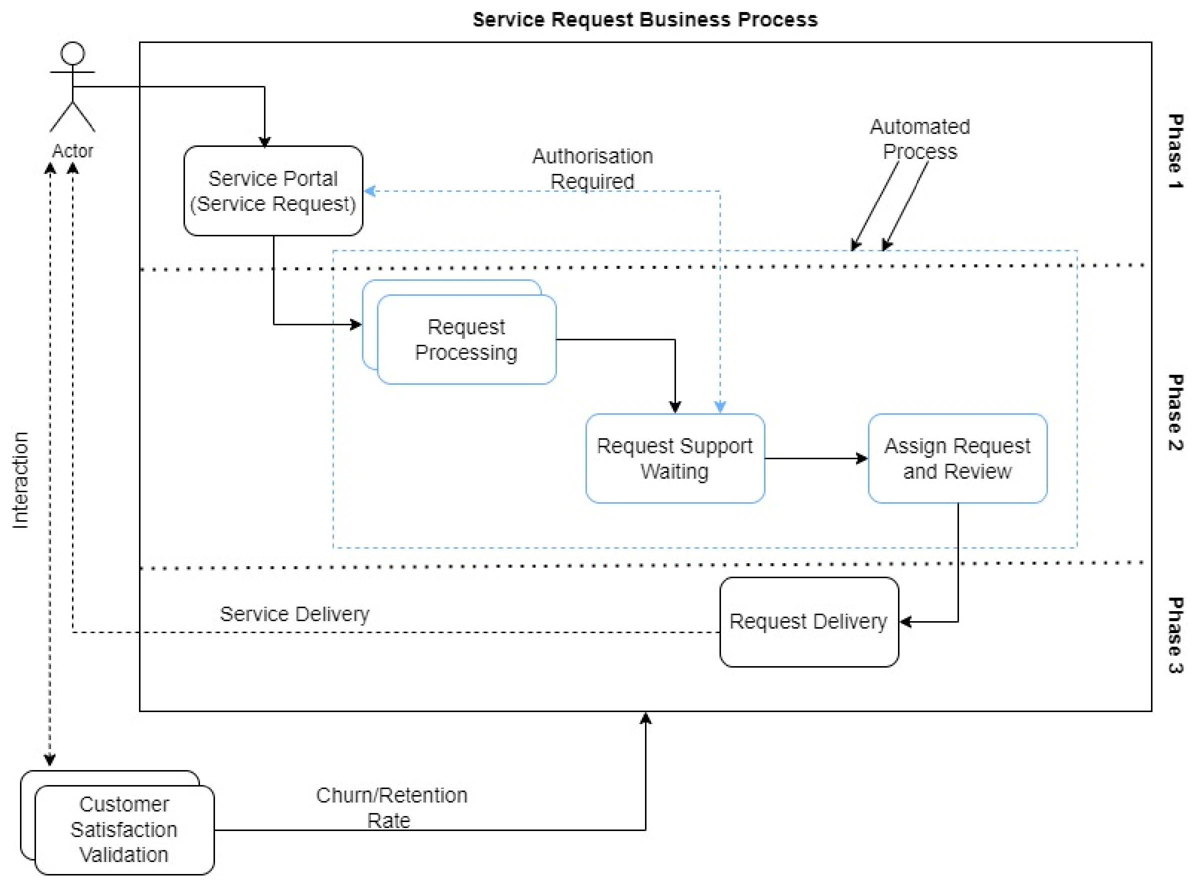


Figure 5. 8 Framework Design for IA Service Request in Web Application

It can be depicted in Figure 5.8., that an actor/user logs in an incident request which could either be for support, categorization, execution, escalation, or closure. The integration of IA platform process speeds up the procedures required based on response to change management principles, therefore meeting high demands of customers, and enabling cost savings via scalability and agility.

5.4.1 The Request Phase

The request phase supports different aspects of requests from the users based on an incident. It ranges from being a support request, to categorisation, escalation, execution, or closure. For each of the process, a highly defined procedure is necessary, as it can be operationalised via tracking. Organisational policies are vital and must be set with regards to making requests as it enables an effective and standardised incident request management for service organisations.

5.4.2 The Automated/Processing Phase

During the automation phase, IA can be described as the main actor as activities occurs within the system. Business processes are enacted without human involvement. IA records requests for the administrator, classifies the incident type and prioritise the requests. Certain times an approval prompt is requested from the management, however due to automation of repetitive tasks, this process is skipped, and each request is allocated to person or a team member in the required department for investigation and diagnoses. After this process has been designated to a team member, recovery can then take place before delivery.

5.4.3 The Delivery Phase

Upon conclusion of the automated phase, the IA system is prompted. This then sends an automated message signal to the user based on the completed request and time of delivery. The system administrator also closes the service request and stores the request into a database for future reference. An integrated IA system in the web application could respond to users' request. This can therefore enable customer satisfaction due to responses in services delivered. It further establishes avenues for better user experience leading to highly intelligent and adaptive decision-making.

Application of IA framework principles for change management system of business processes supports workforce agility by responding swiftly to dynamic technological environments caused by digital transformation. Hence, boosting business performance functions and competitive advantages.

5.6 Implementation and Deployment of WILFUM Dashboard Web Application

The Application developed was given the title WILFUM and this is focused on service organisations and based on the case study of Section 3.4. The dashboard was developed to allow both internal and external users make requests for services and as applied to the organisational business processes.

5.6.1 System Development Approach

In developing the dashboard application system, necessary business processes were considered based on key resolutions for service organisations and enterprise solutions. The first step was to analyse previous dashboard applications and understand its usefulness for service organisations. A vital application fault was that organisations could not assess their agility level for competitive readiness and advantages as well as embed cyber security principles for data safeguarding. This research dashboard application embeds both processes of cyber security practices and measuring agility level based on predefined calculated metrics. It further encourages service request and analysis for organisational performance functionality. The flowchart below illustrates the design and system development for the WILFUM dashboard application.

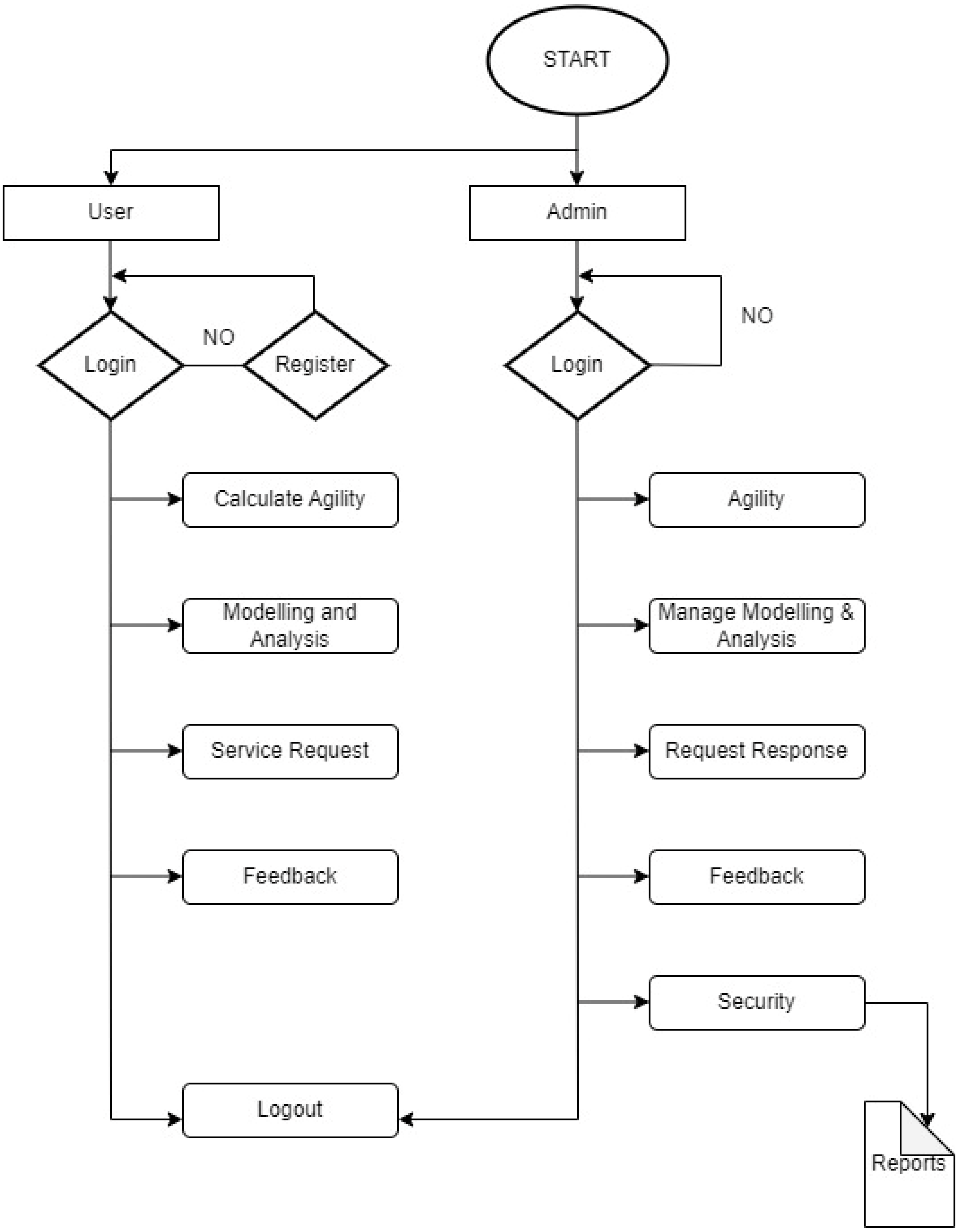


Figure 5. 9 WILFUM Dashboard Application Flowchart

Following the design of the dashboard application the method involved in system development includes the following.

5.6.1.1 System Development Approach Using Oracle APEX

In developing the system, a workspace and schema in Oracle, is used to enable security functions for development. This is called an Instance and it can be found within the administration settings. With the given workspace name, a custom schema was created using the oracle database server. Figure 5.10 illustrates the created APEX workspace within the application for development.

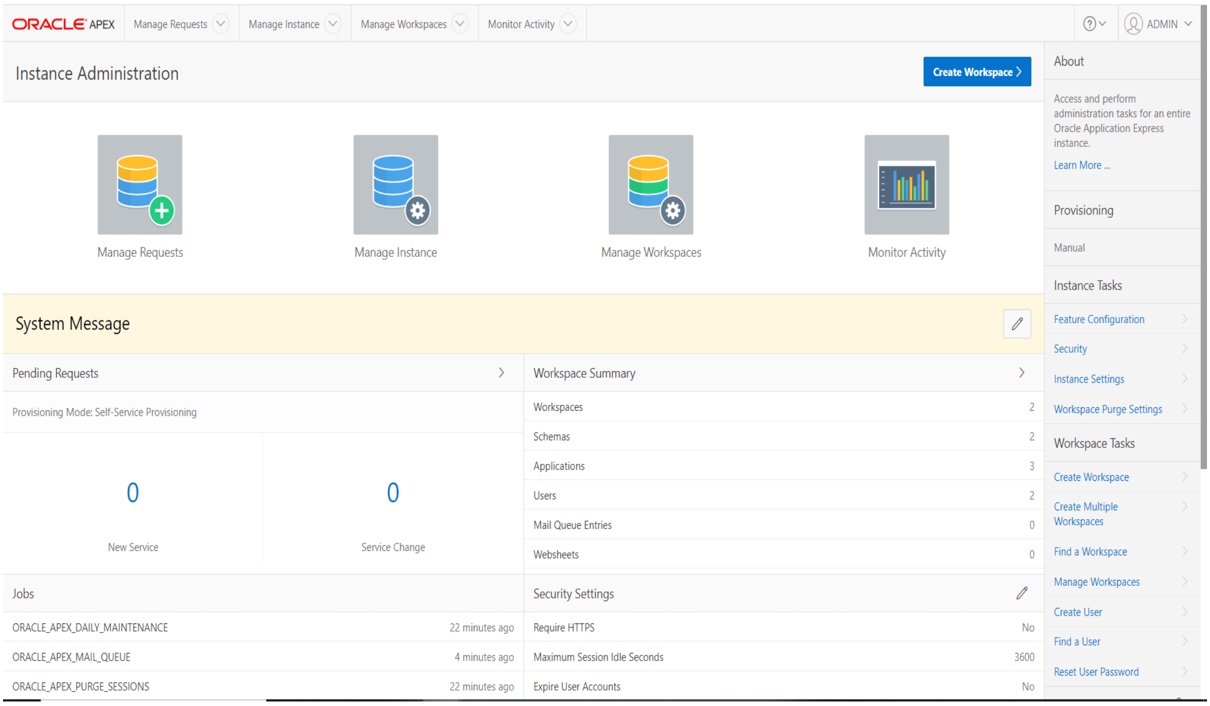


Figure 5. 10 Workspace schema illustrating the APEX Application and Indicating Instance Tasks

Permissions where then further defined before creating a configuration within the local schema for ease of accessibility. Some of the given permissions within the dashboard application, included the enablement of account expiration. For this process, a maximum number of failures had to be stated within the login control. Other permissions within the configuration panel included the enabling of SQL workshop. This allowed the application builder and RESTful services for component availability are shown in Figure 5.11.

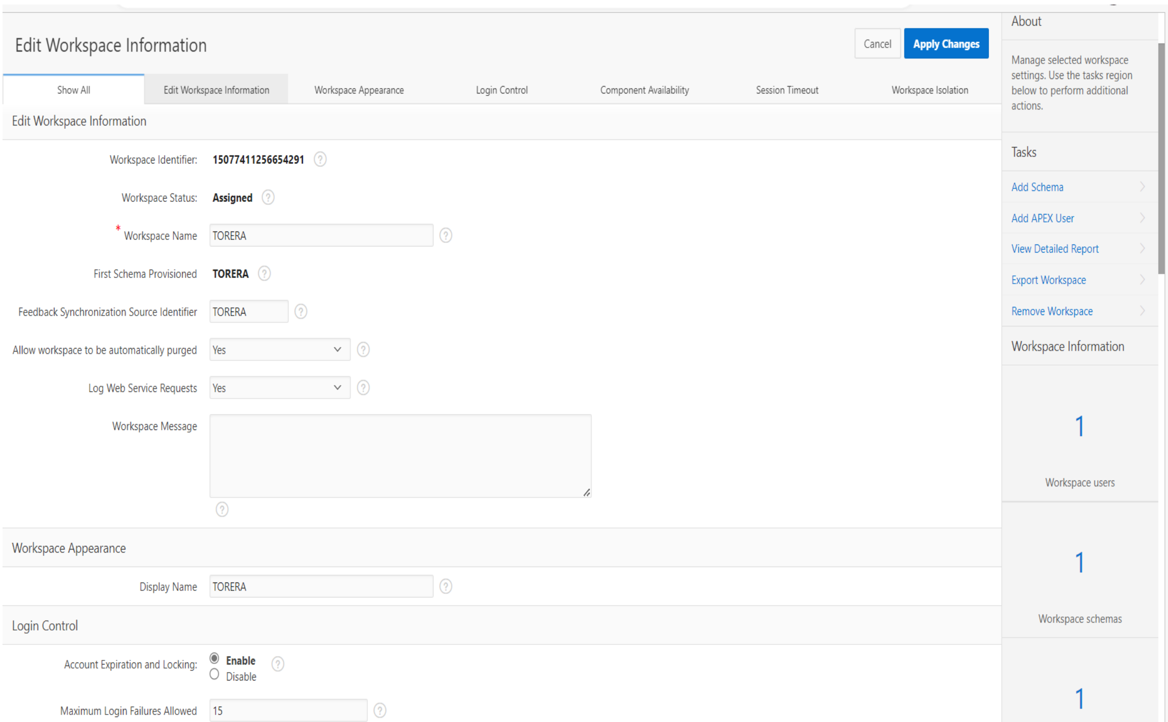


Figure 5. 11 Permissions within the Workspace Information

5.6.2 WILFUM Dashboard Application Page Development

Building each page of WILFUM dashboard application, different processes, regions, items, branches, and dynamic actions were applied. Each page was updated due to its distinguished views and by default, the items on the page were generated using the text items, therefore, updating the items property. The Oracle APEX application wizard also enabled the creation of a process to perform inserts updates and deletes tables within the database section.

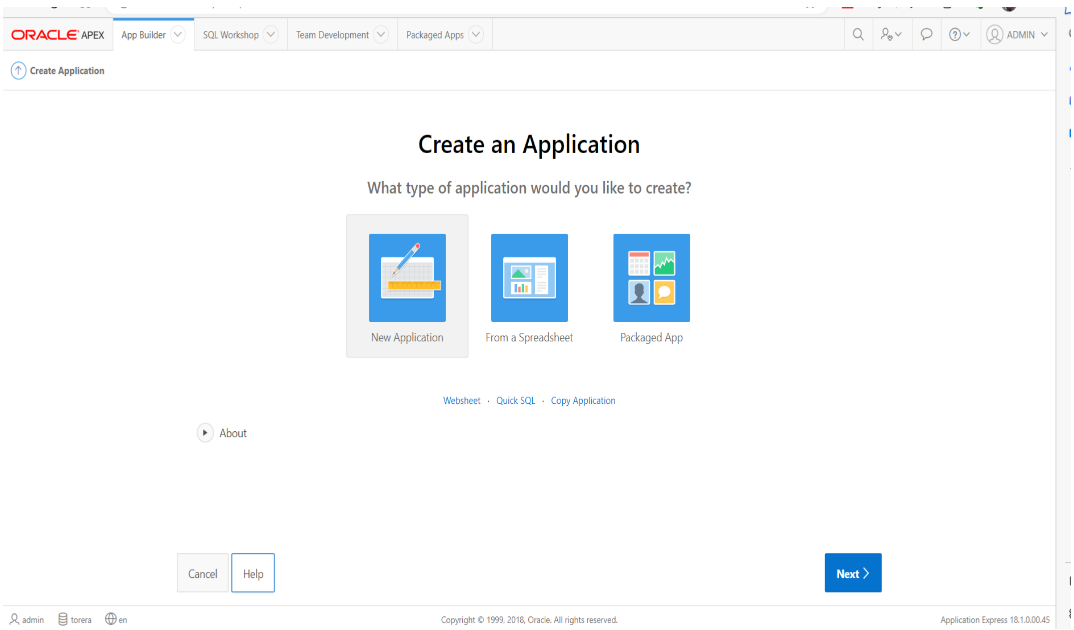


Figure 5. 12 Oracle App Builder for creating a new Application

5.6.2.1 Enterprise Agility (EA) Assessment Page

Measuring EA of organisations enables a better response to changes, and this triggers faster response to technological turbulence caused by digital transformation. Organisations that do not just intend but measure their agility level, do have the ability to raise its profit margins.

Agility measurement for this research were calculated using constructs defined for EA in Section 3.3.2 and 4.3.2. Based on the app, new metrics were developed, and this was calculated based on previous constructs of Agility.

$$EA = \frac{\Delta newTech_{adapt} \;\&\; \Delta quality_{improvement}}{\Delta customer_{demand}}.$$

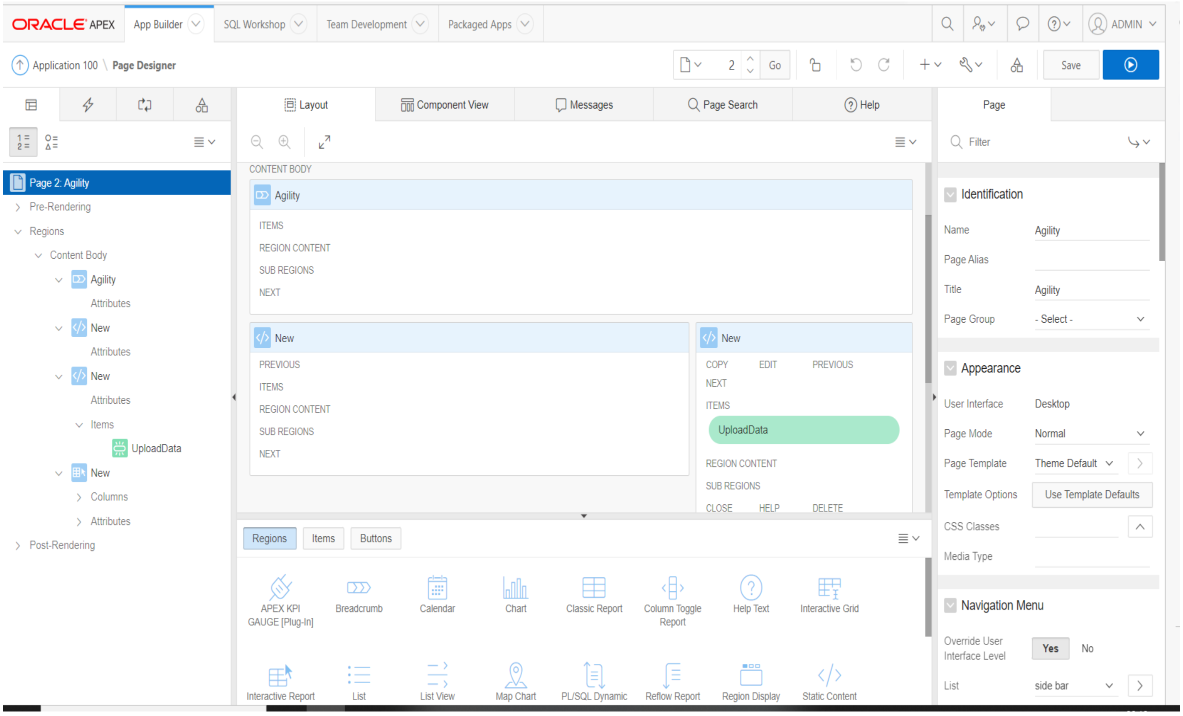


Figure 5. 13 Enterprise Agility Assessment Build up Page

Items used in defining the page for agility includes checkboxes, file browser, image display, number field, percentage graph with text fields. The complete display page for agility is given in the Figure 5.14 below.

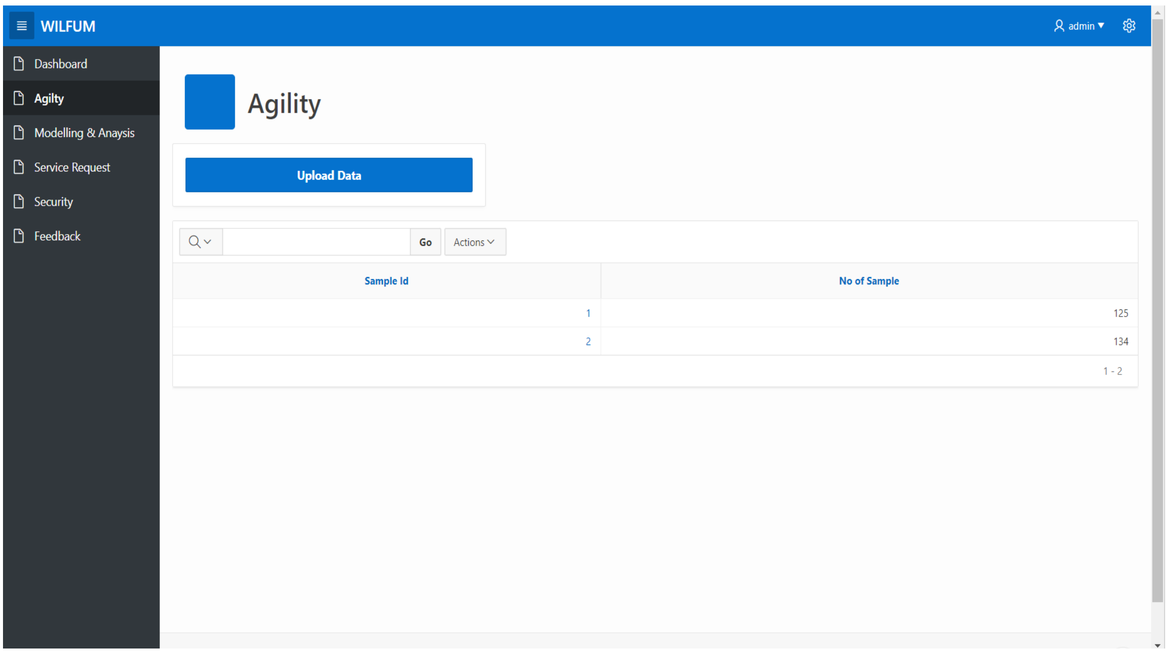


Figure 5. 14 Enterprise Agility Display Page

5.6.2.1.1 Steps Involved in Assessing Agility Level Calculation

To obtain an assessment of an organisation's agility level, there are several steps required. Although may seem like a daunting task, it is very easy to follow as the WILFUM dashboard application has ensured there is ease of use based on aesthetics for users. Images illustrating steps towards assessing agility level can be found in the appendix of the research.

i. The first step is to upload data from a csv. file or copying and pasting of the delimited data.
ii. When data has been uploaded, this should then be further mapped out and sample ID given is no sample ID has been assigned automatically by the system to the dataset in use.
iii. Data validation is carried out to ensure no errors are within the dataset to be loaded.
iv. The final stage before the display of result is the data load results page. Before an organisations agility level is displayed. The data load results state the number of rows with inserted data, updated rows if any was done during the mapping or data validation, failed rows, and rows to be reviewed. Once no error has been indicated, a user can therefore click the finish button to review the agility level of the organisation, and this is illustrated in the image below.

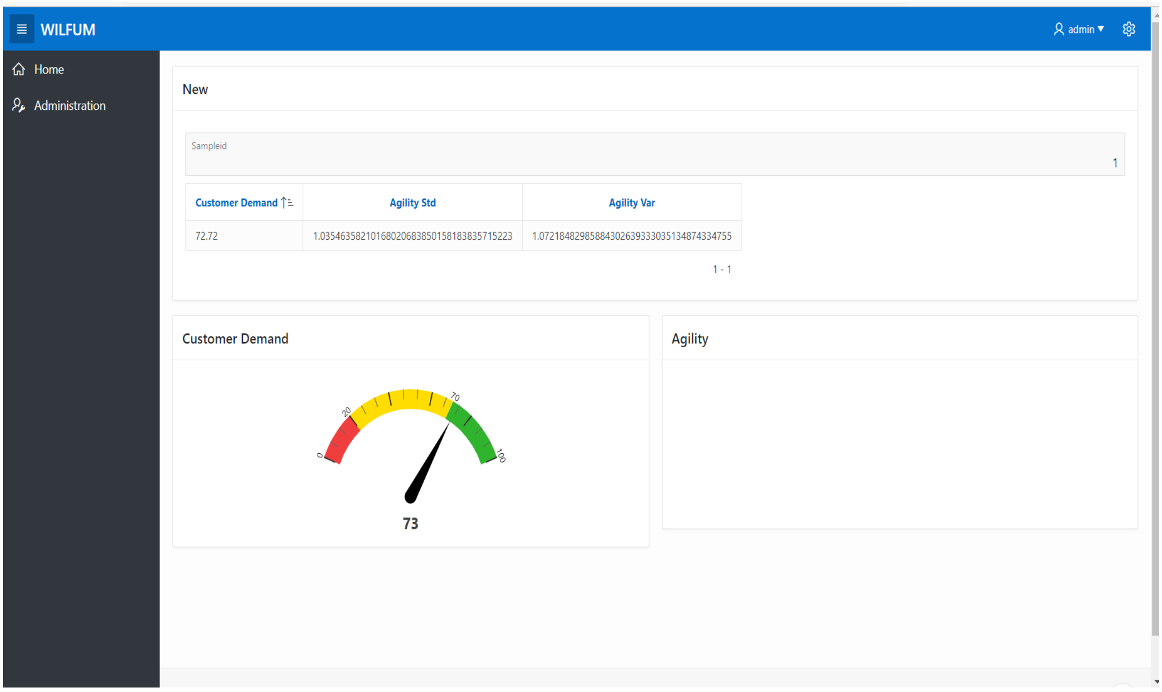


Figure 5. 15 Sample View of Agility level of an Organisation

The Agility Var gives the actual value of EA for the organisation as this has used a variance approach based on the constructs. The image shows that the agility level for the organisation is at a level of 73 percent with regards to customer's demands. Although this is a good level, it is also quite risky for the organisation as a slight drop to this current figure would have to enable change management principles for adaptation to turbulent technological environments.

5.6.2.2 Service Request Management Page

The Service request management used to create incident requests in service organisations. For every incident created an automated signal initiates the incident request and passes it to the administrator as described in section 5.5 above. The Layout and component view for developing the incident request can be found in the appendix of the research as it illustrates the incident form that was designed as well as page rendering, buttons, dynamic actions, and processes used. Incident ID was hidden from the user's view on the incident form as this enables the admin keep track of every incident recorded for security and auditory report purposes. The Figure 5.16 below illustrates the incident form that users can create in service organisations.

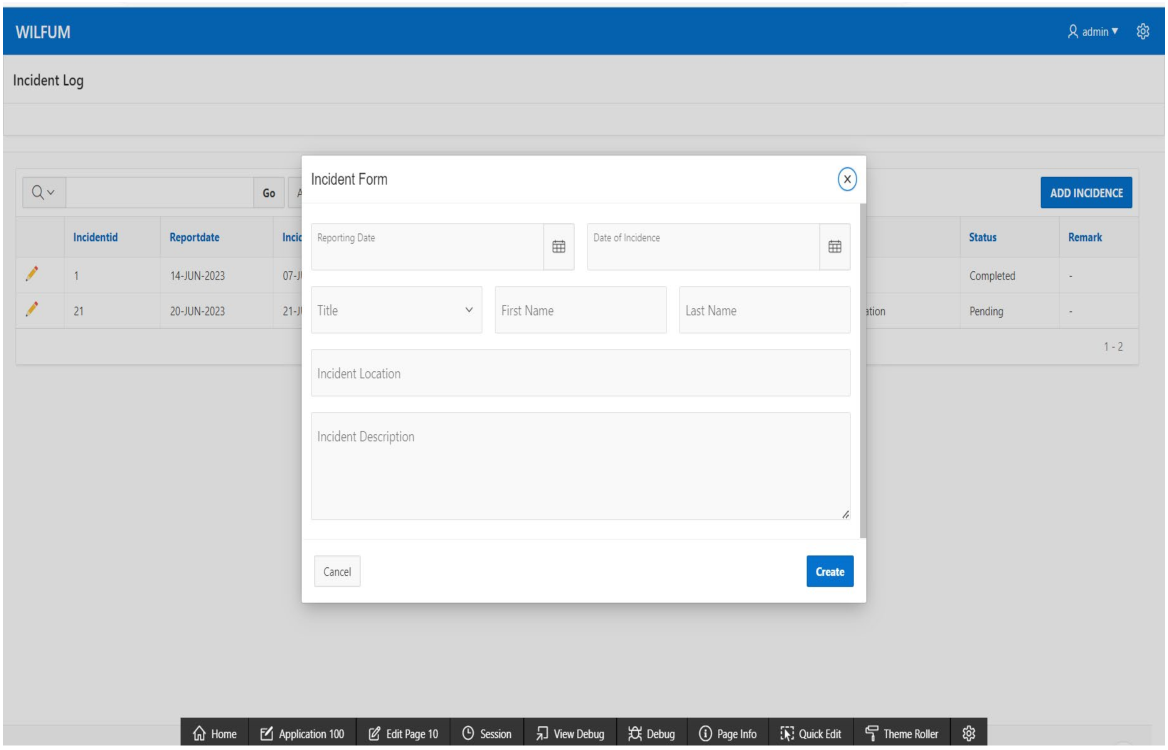


Figure 5. 16 Service request Incident Request Form

5.6.2.3 Feedback Collection and Analysis Module Page

Feedback enables the improvement of the WILFUM application for further usage. It grants users the advantages of giving their user experience and any feedback comments based on any aspect of the organisation.

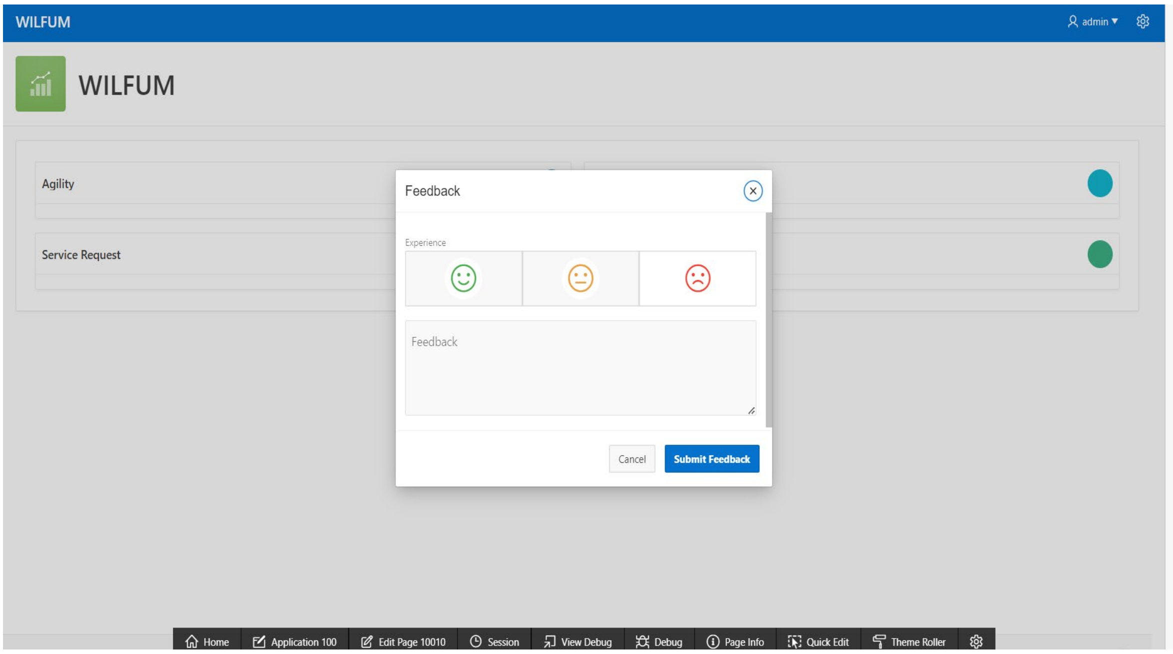


Figure 5. 17 Feedback form for User Experience and Comments

5.6.2.4 WILFUM Dashboard Reports and Analytics

It is important to analyse reports generated for security purposes. The WILFUM dashboard application ensured the utilisation of the SOAR platform for remediated actions [85]. The application also ensured activities based on service case management such as incident response logs were embedded for organisational monitoring of activities within the service request systems. Therefore, this supports end-to-end management with regards to intelligent decision making. To prevent cyber-threats and vulnerabilities the reports logs help to detect and analyse different indicators of compromise. In designing the WILFUM application, the following activity reports have been considered and as illustrated in the diagram below, can only be seen by the system's administrator. All other report analytics can be found within the appendix of the report.

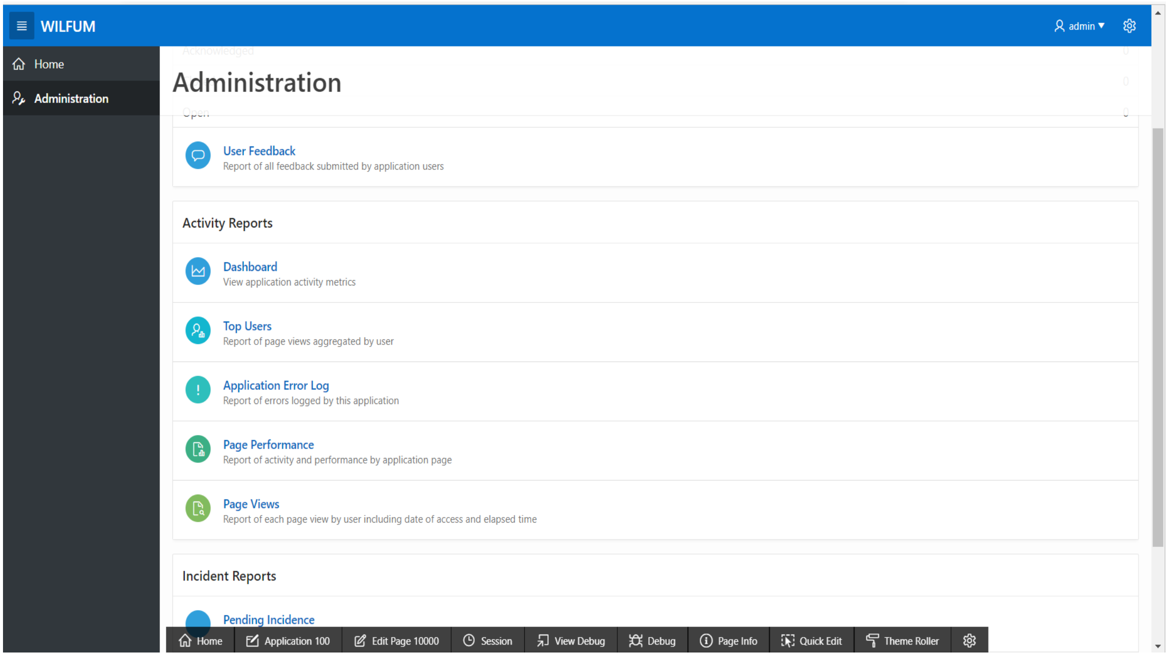


Figure 5. 18 Administrative Page Displaying User Feedback, Activity Reports, Incident Reports

5.6.2.4.1 Dashboard Reports

The dashboard report considers the application metrics on hours spent on pages in the application, top users of the application, most active pages, recent errors, and latest activities carried out within the WILFUM application.

5.6.2.4.2 Top Users

The top user reports accounts for views aggregated by each user that accesses the dashboard application. It can be viewed in either a pie chart format or hourly access per user.

5.6.2.4.3 Application Error Log

Application error log of the WILFUM application takes account of users affected, its occurrence, the message of event that occurred, the context of what aspect of the application was affected, and the affected component of the application. This report can also be graphed and downloaded using either a .csv format, HTML, email, or PDF format. A sample .csv format of the application error logs can be found in the appendix of the application.

5.6.2.4.4 Page Performance

The page performance report measures median elapsed time to open a page. It also investigates through exploitation, distinct users, application sections and the numbers of page views.

5.6.2.4.5 Page views

This report aspect investigates each page views by users and it further includes the date of access and elapsed times.

5.6.3 Testing and Quality Assurance

Testing and quality assurance ensured that the web application functions correctly to suit its purpose of use. The Oracle APEX app uses an automated function testing script for its baseline versions [127]. The application focuses on performance testing and when carrying out a test it automatically checks each page of the application based on attributes, checks, categories (which is majorly security), provides values and messages if any within the checks. Figure 5.19 below indicates a screenshot of the performance testing carried out on the WILFUM application. It can be denoted that the application test was carried out on all pages created within the application.

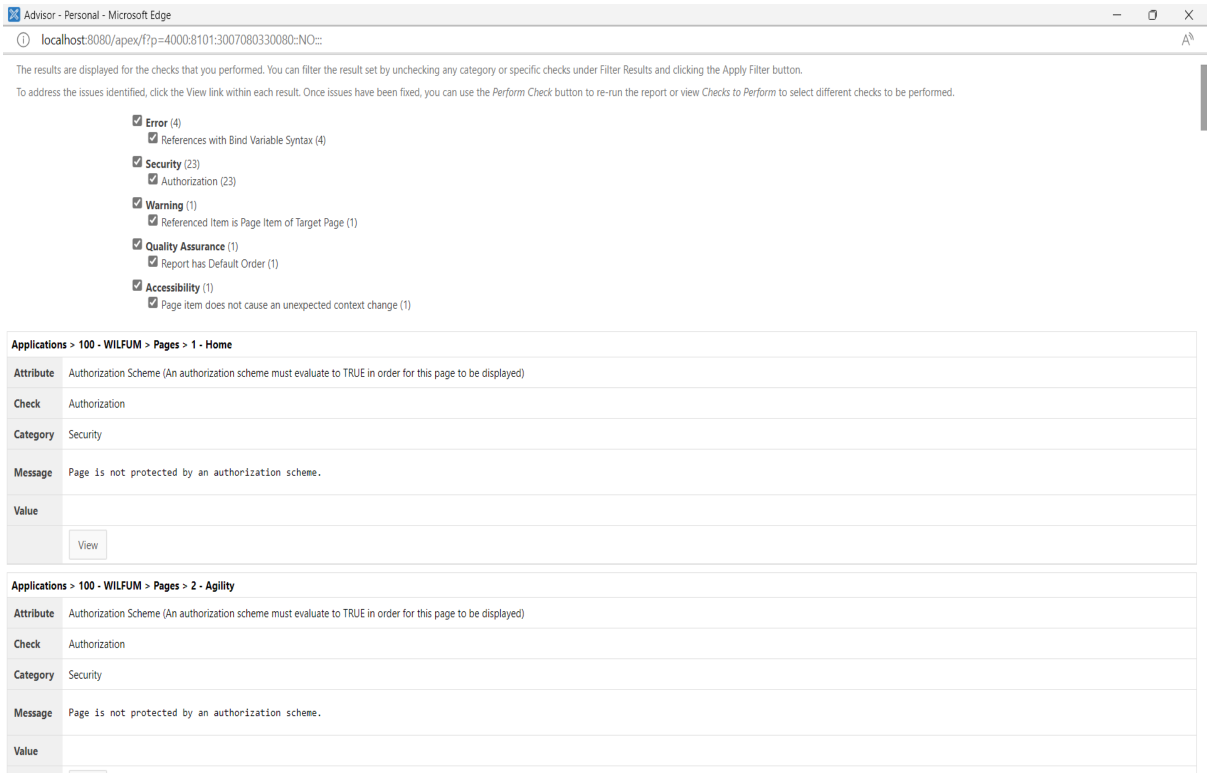


Figure 5. 19 Performance Check Test on WILFUM Application, Implemented Using Oracle APEX

5.6.3.1 Application Testing on Case study

The WILFUM application was further tested on the case study to measure its agility level based using sample data from it database. This yielded different agility level results ranging between 50 to 60 percent with regards to customers' demands. Therefore, indicating that the organisation needed to implement change management principles for agile practices towards its business processes. The application also worked effectively for service request management, feedback analytics and reporting which is useful for security measures against cyber threats. Appendix G., indicates an email received from the business development manager of the organisation, recommending the application as it performs all functionalities as required towards the organisation's adaptation to technological turbulence for change management practices.

5.7 Summary of Application Development for Agile Processes

This section concludes the WILFUM web-application development process. Focusing on the development and implementation of the dashboard web application. Following the system design and framework architecture, the research considered a low code application known as Oracle APEX to develop and implement the required flowchart design of the web application. It then builds on IA and considers the SOAR platform for automated and security purposes. Constructs of EA previously discussed in chapter 4 are utilised as metrics for assisting organisations to assess their agility level. Incident requests can also be performed, and feedback collected towards application improvement. Cyber security is crucial in-service organisations, and the implementation of error logs and reports enables analysis of reports for prevention of threats and vulnerabilities to service organisations.

The WILFUM application and this chapter provides a huge scientific contribution to service organisations as it gives organisations the ability to assess its agility level and shows a range of weak to good agility, therefore enabling organisations to act swiftly when there is a drop in its agility level for competitive advantages. The application further utilises factors of IA for intelligent decision making and creates advantages for swift response to cyber threats with regards to its agile processes. Therefore, it can be easily adopted by service organisations in responses to various incident response to service requests whilst improving customer experience therefore enhancing customers satisfaction and improving strategic and operational competitive approaches.

Chapter 6: Discussion, Evaluation, Limitations and Research Contributions

6.1 Introduction

Following scientific contributions across different enactments of emerging technologies (ET) for agility processes in services organisations across chapter 3, 4, and 5, the major focus of the thesis is the adoption of the WILFUM application by organisations into their business process for early detection of technological turbulent and application of change management principles and policies for competitive purposes.

This concluding chapter elaborates further on the results achieved of the analysis presented in Chapter 4 and the WILFUM Application in Chapter 5, major findings within the thesis, limitations, future work and concluding remarks. It particularly discusses the research usefulness in the academic environment and for practitioners. EA applicability in organisations cultural practices can trigger faster decision making and enhance competitive advantages. Furthermore, this chapter discusses the benefits of the study, limitations encountered during the research, and it highlights unique contributions based on enterprise agility as an intermediate for competitive purposes, based on emerging technologies. The research then revisits each research question mentioned in Section 1.4 and states how the individual research have been able to answer the questions based on the objectives of the research and suggest avenues for future research studies.

6.2 Emerging Technologies (ET) and Its Impacts on Business Processes: Contributions of Literature Review

As discussed in sections 2.6 and 2.7, the review process has been able to indicate theoretically for practice and academics that the addition of a meditator towards business process infrastructural system, speeds up organisational sensing and responding capabilities to technological turbulence. It has also indicated that the utilisation of IA within process systems of organisations also reduces error due to human abilities and increases organisations adaptability to disruptive technological environment. Furthermore, IA enhances EA functionalities adaptable to organisational business processes, whilst enhancing organisational awareness to reduce vulnerability to security threats.

6.2.1 Aligning RQ1 to RO1: *What factors influence emerging technologies for business process capability and how can they be utilised to attain maximum business operational performance?*

A major goal of this research was to understand the concepts of the featured emerging technologies based on its influencing factors to attain maximum operations in business processes. This question was answered in Chapter 2 as a systematic approach was used to understand the concepts of BDA and mediators that could influence emerging technological concepts with a major focus on EA. The research also investigated through exploitation intelligent automation and security awareness for agile purposes. Based on the research question answer, it was discovered that theoretically there was a positive relationship between BDA and OP, and it had an impact on organisations in effective decision making. The research also indicated that in attaining effective business operational performance, the use of a mediating or moderating effect improved change management practices and supported adaptation of business processes for IT/IS infrastructures in organisations. With recommended topics for future research, the research indicated that opportunities could provide further functional insights on BDA adoption into organisations, for strategic standardisations and interoperability to business-driven and technologically driven changes for competitive advantages.

6.3 Impacts of Big Data Analytics (BDA) and Enterprise Agility (EA) for Customers satisfaction (Cs)

The utilisation of BDA and EA can enable organisational adaptability towards changes and hence, encourage better managerial insights towards effective decision-making for adoption. Based on regressive analysis, it can be summarised that this research work offers useful contributions towards knowledge on the impact of BDA for performance, using EA as a mediating effect. The research study was able to integrate some key aspects of limitations and future work, based on different research fields from previous literature. A major aspect of this research was built upon research by [29], this study stated, further work should investigate through exploration antecedents to understand the relationship amongst the variables of BDA, such like ambidexterity, agility, and performance. This formed the basis of the research focus as understanding the inter-relationship amongst variables could help in improving organisation's operability for intelligent decision making based on agile purposes. Furthermore, it also indicated factors that affected agility of organisations and paved a way towards application building for agility calculation.

Building upon the hypothetical model as illustrated in section 3.2, a positivism theory illustrated that a positive impact of BDA as an emerging technology had a positive effect in stimulating enterprise agility of organisations which in turn affected performance output with regards to customers satisfaction for productivity and market growth. The research hypothesis was based upon previous literatures and as adapted from research by [6] which called for further research to use specific analytical methods towards business analytical application for business data process investigations.

Using an SEM approach to understand the interrelationship amongst variables, it is important to understand the key driving forces for an efficient business process. This idea could improve performance and enable faster response to dynamic changes. Therefore, the need to integrate into the hypothetical model a mediating effect became vital as research by [52] indicated that there were direct and indirect effects of BDA capabilities on business model innovation. The research model further called for the investigation into other mediating variables as this posed a major key limitation to the research study.

Following these research indications, this study then focused on answering the *RQII,* to understand factors that influence agility based on Cs for performance due to productivity and market growth.

6.3.1 Result Discussion and Implication of Big Data Analytics (BDA) and Enterprise Agility (EA) Impact on Customer's Satisfaction for Performance

Based on the linear regressive analysis in SEM, it can be summarised that this research work offers useful contributions towards knowledge on the impact of BDA for Cs based on performance, using EA as a mediating effect Theoretical findings indicated is evident to positivism research on the impacts of mediating effects for performance purpose in organisations [30], [128]. As mentioned earlier, this approach was adopted into the research model design for regressive purposes based on analysing the inter-relationships amongst each variable constructs. Empirical results gathered demonstrate all variables, that is, BDA, EA, OP and Cs are inter-related as BDA increases EA of organisations. The results also indicate the relationship with regards to standardised measurements for agility in responding to technological turbulence caused by emerging technologies. As findings are in correlation to previous studies, the research study investigating the interrelationship amongst variables offers insights for Cs with regards to performance due to productivity and market growth.

Although studies on the impact of BDA for organisation's performance has been investigated in the past [14], [52], it can be argued that these studies have not tried implementing customers satisfaction into its designated research aim for performance due to productivity and growth. Furthermore, EA is a common concept amongst academics and practitioners, however, research on the utilisation of agility as an intermediate for information system infrastructure of organisations is limited as solutions could enable organisations understand attributes that enable its sensing and responding properties to technological turbulence. The aim of this research section was to explore the interrelationship amongst BDA and EA for Cs based on OP for profitability and market growth based on the given hypothesis results could improve system capability for intelligent decision making based.

It is a good practice to record all SEM results based on estimation and modelling processes, However, it can be noted from previous articles that most researchers that utilised SEM for analysis fail to carry out a multivariate normality assumption for investigation of internal consistency in data. Also, based on a linear regression, the results gained from the measurement model validation indicated that the overall fit of the hypothetical model was good as majority of the results fell within the standardised measurements [110]. Factor loadings, standard errors, p-values, and representation of the model indicated a strong relationship amongst each variable and as indicated in the appendix, the results also considered similar relationships amongst variables and constructs within the research models which could be considered for future study.

6.3.1.1 Experimental Metrics for Model Measurement using Structural Equation Modelling

During the research experiment, four different metrics were used to design the measurement model for the research. This was considered to exemplifies the hypothetical measurement model. Each metric calculation was to measure the variable within the research, and this was defined by its constructs.

Big Data Analytics was defined by its attributed capabilities, and this was made up of the volume of data within the system, value creation, tools measurement and product optimisation.

Enterprise Agility considered factors that are attributed to effects in changing environments, and this included the demands of customers, adaptability to new technologies, an improvement in quality (which was disregarded in SEM as not a valid construct) and regulatory price review.

For Performance purposes of organisations, the profitability gain, market growth and returns were used.

In representing customer's satisfaction, the feedback based on customers response, product recommendation and quality improvement were used to define the variable.

It is important that practitioners should be able to quantify these variables with respect to their organisations to determine their agility level as this information may be useful in adaptability to changing environments due to ET disruptions.

6.3.1.2 Theoretical Implication of Enterprise Agility Research for Competitive Advantages

Result findings proved contribution to knowledge, and as indicated on how BDA and EA are interrelated. This in turn influences performance of organisations positively, which was based on the hypothetical model developed. Therefore, providing insights for capability processes. The approach used can be adopted as unique sequence of operation to IT/IS organisational systems. This was exploited on the interrelationship between BDA capabilities, EA, OP and Cs. The results provided insights for adoption of EA in organisations, as this can enhance stability in organisation's performance during technological uncertainties. The ideas utilised were based on survey findings and as to improve satisfaction of customers in an organisational context. It can therefore be stated that there is need for organisations to invest more on BDA, by exploiting all necessary avenues for profitability and market growth. It is also evident that organisation's ability to exploit adoption of EA would further enhance its ability to adapt to changing environment, and improve decision making processes [4]. This research study has provided answers to the *RQII*.

Using a hypothetical approach based on a case study and model development, the study has also been able to evaluate each construct of variation based on variables of BDA, EA, OP and Cs. This is contrary to previous studies of [15], [32], [39], [128], as investigation on the impacts of BDA on performance had certain limitations and called for area of further work which has been implemented in this study. This research study used an SEM approach whilst considering multivariate analysis which was not done in either of the research mentioned above. This was useful to understand the inter-relationship amongst variables in the model between the variables of BDA, EA, and performance for profitability and market growth. Findings indicate there is a growth based on positive effect, whereas influences on BDA and EA, can improve performance of organisations.

6.3.1.3 Practical Implications of Big Data Analytics for Competitive Advantages using Enterprise Agility as a Mediating effect for Customers Satisfaction for Performance Purposes

Enterprise Agility (EA) as a mediating effect, continues to play a significant role towards advancing BDA for performance purposes in service organisations. Although, previous studies have empirical evidence of BDA for performance advantages, this research contributes towards understanding of the variable linear relationship of BDA within an organisational system and EA for Cs due to performance on profitability for market growth and productivity. Using a Structural Equation Modelling (SEM) approach, the results have also shown that agile systems adaptation to technological disruptions are important factors for responses to dynamic changes. This is caused by Emerging Technologies (ET), and as useful for market growth, which is indicated in BDA [*H1*], as influenced by the EA positively, but only based on positivism. Findings have also indicated that capabilities or constructs of BDA variable on EA play a crucial role towards organisational development and provides reactive responses to changes due to its linear relationship. These can be traceable to frequent employee training, on new and advanced technology, which is based on the understanding exploiting ET for organisational benefits. This can enable optimum performance, therefore, leading towards organisational profitability for customer satisfactions [14].

The research has also been able to show that the use of an intermediate, EA, helps in creating stability in technological turbulence. This is based on the considered case study in section 3.4 of Company X and as specific for service organisation. The hypothetical approach further creates initiative for stronger positive effects, towards organisational performance in [*H2*] as it also encourages profitability and market growth in [*H3*]. This research idea can bring about high value returns on investments towards business process application and maintenance for agile processes. As organisations continue to implement business processes on IT/IS application platforms, it is encouraged that service organisational managers should understand procedures on how to rely on the capabilities of BDA, to improve stability and adaptation to changes.

6.3.2 Aligning RQ2 to RO2: *Are the underlying variable model of BDA and EA interrelated; and how can they influence Cs due to productivity and performance in service organisations?*

Based on its prominence and previous research which suggests that an increase in technology improves the performance of organisations, this research study explored an important gap in academic literature [6], [14], [32], and provided insights on the implementation of BDA for profitability and interrelationship variables between Information Systems that could aid performance optimization in a business process. Building upon previous literatures and findings, this research then proposed a hypothetical model that is based on a case study used as (Company X). It concluded that there is a linear relationship between variables of BDA and EA and thus, providing positive influences on performance. Furthermore, it can be stated that the utilisation of BDA and EA can enable organisational adaptability towards changes and hence, encourage better managerial insights towards effective decision-making for adoption.

6.4 Security and Intelligent Automated web Platform: A Dashboard Application for Service Organisations

The major aim of this research was to exploit emerging technologies to create an agile and effective technological platform for change management practices, operational stability, and digital transformation based on policies of SOAR policies. Based on the application built, the main aim of the research has been covered such that it has enabled organisations in calculating its agility level, whilst adhering to SOAR policies for service organisations based on incident response and cyber security procedures for feedback and report analytics. The application enables administrators in service organisations to investigate error logs based on the analytical dashboard application to prevent cyber threats and vulnerabilities to cyber criminals. It also enables both administrators and users to assess organisation's agility level, record incident and provide feedback for future development. Whilst building the application, certain conditions were set in place through instances for security purposes. With a user profile and admin, the application enables users to provide a predetermined username and password for security purposes before granting accessibility. The design of the application was done with a low-coding environment for adaptability of IA platforms.

6.4.1 Good Utilisation of Dashboard Application

It is recommended that managers of service organisations adopt the WILFUM application as this can enable them to assess their agility level for intelligent decision making in competitive environments. The functionality and ease of use of the application has been carefully taken into consideration, as the WILFUM application is expected to improve insights for performance purposes and reduce threats due to cybercrimes in service organisations. The application used the Oracle SQL database for back up and maintenance of important information as every information gathered must be maintained and preserved for future use due to security policies.

6.4.2 Practical Importance of WILFUM Dashboard Application

As mentioned earlier, it is important to develop an improved system capability for intelligent decision making based on agile approaches towards handling complex environments caused by emerging technological disruption. Previous research has carried out several empirical research on BDA and OP. However, no study has thought about implementing an analytical application that can either measure agility or respond to incident in service organisations. Therefore, this research section makes this a unique contribution for performance purposes and practice. The key towards successfully implementing the dashboard was ensuring that that the application could automate through some human tasks to reduce redundancy. Another key which was quite important was the ability to implement a security framework based on Intelligent automation for capturing every element of the application. The application enabled a report system that considered error logs based on true positives or false positive to security threats.

The WILFUM application follows a procedural step towards its accessibility. First a user is asked to log in by requesting for the right credentials to be inputted. If the user is wrong, the system will fail but due to it been an offline application and not live, the users were given the opportunity of trying the password 15 times before failing. This could always be edited in the admin section when connected to a live server. If put through, the user is faced with the menu page and menu options to which any functionality within the system can be used. The WILFUM app is quite important as it helps service organisations though performance optimisation for competitive advantages.

6.4.3 Aligning RQ3 to RO3: *How can an intelligent system be developed to improve operational capability of organisations and how can strategic decision making be enhanced?*

Using Oracle APEX as a base application for development of the WILFUM dashboard application, answers to this research question provided new insights for adoption as previous research only theoretically represent agility experimentally, however, no research has been able to provide a standardised calculation for service organisations adoption, for adaptability to changing environment caused by technological turbulence. This research developed a framework for security response to incident and this was also embedded into the dashboard application. Outcomes indicate that service organisation upon adoption of the application can measure its agility level and respond to changes when it notices a decline in its agile functionality. Also, it also assists practitioners in determining the factors that affect agility, there improving its competitive advantages.

6.5 Thesis Contribution and Key Areas of Research Study Application

This research has recorded significant impacts for change management practices and security advancement in service organisations, which is viable for practices and knowledge management in the field of Computer Information Systems. The following sections discusses the thesis contributions, as well as points out key areas useful for adaptation in business processes of service organisations.

6.5.1 Achieved Key Area of Research Study

The research study investigated 2 emerging technology types (BDA and IA), based on agility processes (using EA functionalities) for effective decision making in organisations. It has contributed uniquely by achieving the key area of study to the scientific community of computer information systems whilst achieving its aim.

i. The hypothetical view on the impacts of BDA and EA for Cs based on OP for market growth and profitability has been mentioned, and an extensive theoretical review with regards to related works has provided insights for development and future research.
ii. The scientific theory grounded on agility processes and techniques, and its application to emerging technologies have been subjected to peer review and

publications are listed in Appendix A. The publications have also been cited by other relevant articles useful for academic knowledge and organisational practices.

iii. An empirical investigation to understand the inter-relationship amongst variables of the hypothetical model has been tested and as detailed in Chapter 4.

iv. New insights for adoption based on unique contributions for the WILFUM dashboard analytical application has been mentioned in Chapter 5. This is useful for service organisations in measuring their agility level for competitive advantages, and it has provided avenues for development and enhancement for agility predictability.

6.5.2 Thesis Contribution for Industrial Practices and Academic Knowledge

This research thesis has contributed uniquely to knowledge, towards understanding the usefulness of agile processes for business model infrastructure and enhance industrial change management practices for competitiveness. It has also created an analytical dashboard application that can be adopted for service organisations in measuring its agility level whilst performing service request functions both internally and externally.

The major contribution of the thesis is as follows based on key achievements.

1. Contributions to Academy and Industry
    - i. Adoption of BDA in organisations can enhance stability in organisation's performance during technological uncertainties as it has proved that the hypothetical model is valid.
    - ii. The use of SEM has indicated that there is a true interrelationship amongst variables of BDA, EA, OP, and Cs and it is extremely vital to use a mediating effect to improve organisation's agility (Chapter 4). Therefore, practitioners can adopt agility practices to improve its sensing and responding capabilities.
    - iii. A framework for security awareness based on incident response process in service organisations was designed and this was implemented into the dashboard application (section 5.4).
    - iv. The novel research was the development of an analytical dashboard application which can be used in measuring agile levels and enhancing service organisation requests and report feedbacks using an IA and SOAR platform and principles respectively (Chapter 5).

6.6 Research Limitations and Future Work

During the thesis, some limitations were encountered, and this can provide a new avenue for future work arising. This section explores the limitations encountered in the research and discusses further work that can be done to ensure that the limitations can be mitigated.

Based on the analysis of BDA and EA for Cs, A Structural Equation Modelling approach on Variable Interrelationship, a major limitation that occurred was the data sample size and no generally accepted standardized statistical assessment for SEM models. Numerus academics have continued to argue on a standardised accepted values for statistical significance in SEM. Also, the sample size although may seem low with a goodness of fit, academics still argue on accepted values for sample sizes used. Also, a second limitation would be to perform the research over a cross-sectional period for full validity during research assessment.

Investigating the literature review, recommended research topic for further research has been presented in section 2.8. This will enable organisational innovation and adaptability for practises.

Further work would be to perform a system dynamics model in real time to understand the inter-relationship amongst the variable constructs as presented in Chapter 4.

The analytical dashboard application should be built to large scale and tested in large enterprises on organisational services as it is highly recommended for agility enhancement and adaptation to changing environments caused by technological turbulence.

6.7 Chapter Summary, Concluding Remarks and Conclusion

This chapter has discussed the applicability of agile processes for business enhancement based on the utilisation of BDA and IA as emerging technologies for business process models. The research was able to investigate the interrelationship amongst each attribute that make up variables, as required to examine the hypothesis validity for development and use. Based on the results, the dashboard analytical application was developed using Oracle APEX to help service organisations in measuring its agility level for adaptation to technologically turbulent environment caused by digital transformation disruption. The application also offers better insight for adoption as it considers, security practices and policies. It can be suggested that adoption of the WILFUM application will aid intelligent decision making and enable agility functions of organisations based on swift dynamic response due to change management principles.

6.7.1 Concluding Remarks

The research presented in this thesis demonstrates the credibility of developing a hypothetical model for customers satisfaction due to performance of market growth and profitability. It also illustrates the impacts of emerging technologies for performance whilst using enterprise agility as an intermediate. The research was split into different sections. The first section was to systematically analyse literature to understand the concepts of the two considered emerging technologies which are Big Data Analytics and Intelligent Automation. It also tried understanding the effects of moderators on enterprise agility whilst answering a significant research question. The second phase focused on further works and limitations of previous research and developed a hypothetical model to understand the inter-relationship amongst the variables within the model. It also used an SEM approach to analyse the relationship linearly based on a regression model. The third and final phase of this research then used an Intelligent Automated Platform and based on the principles of security orchestration, automation response to develop an analytical dashboard approach, which was a new insight for service organisations and adoption could help organisations enhance its agility practices for adaptability to technological environments.

6.7.2 Conclusion

This thesis has been able to achieve 2 important goals to which comprehend contributions to science. This includes the 3-main research questions and research publications in the field of research. The first goal was achieving each research objectives with regards to emerging technology. This formed up theoretical contributions and practical implementations for academics and practitioners for adoption of agility processes and practices for competitive advantages. Furthermore, the second goal was unifying both emerging technology types for analytical application development which formed the unique aspect of the research work. Also, it can be deduced that the research has given rise to publications which have been cited relevantly by other articles, therefore indicating the research's relevance in the field of computer information systems.

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Appendix A – Research Publications

Conference Publications

1. O. C. Williams and F. Olajide, "Towards the Design of an Intelligent Automation Framework for Business Processes," *2022 5th International Conference on Information and Computer Technologies (ICICT)*, New York, NY, USA, 2022, pp. 13-17, doi: 10.1109/ICICT55905.2022.00010.
2. O. C. Williams and F. Olajide, "A Technological Approach towards the Measurement of Enterprise Agility," 2020 15th Iberian Conference on Information Systems and Technologies (CISTI), Seville, Spain, 2020, pp. 1-4, doi: 10.23919/CISTI49556.2020.9141142. (Ci
3. Williams, O., Olajide, F., Al-Hadhrami, T., Lotfi, A. (2020). Exploring Process of Information Systems and Information Technology for Enterprise Agility. In: Saeed, F., Mohammed, F., Gazem, N. (eds) Emerging Trends in Intelligent Computing and Informatics. IRICT 2019. Advances in Intelligent Systems and Computing, vol 1073. Springer, Cham. https://doi.org/10.1007/978-3-030-33582-3_98
4. O. C. Williams and F. Olajide, “Intelligent Automation and Cybersecurity Procedures for Business Processes”, 2022 ICITST in cooperation with WorldCIS, WCST, WCICSS-2022.

Appendix B – Ethical Form

School of Science and Technology

Non-Invasive Human Ethics Committee

Notification of Decision– 19/20-46V3

Date: 27.04.2020

Student's Name	Olatorera Chidozie Williams
Supervisor's Name	Dr Funminiyi Olajide
NTU ID	N0643847
Course	Computer Information Systems
Title	Analysing the Impacts of Emergent Technology on Enterprise Agility using System Dynamics Modelling
Start Date	23.04.2020
End Date	22.04.2023

Approved with Recommendations - see points below. Before commencing your research you may want to incorporate these suggestions and if you do make any changes you must return the final version via SST.ethics@ntu.ac.uk so that the correct version is in our records.

Points the applicant needs to address:
Independent Reviewer 1: Approved with recommendations • 2.2: 'Working class' should simply be participants will be 'employed' by… • 6.3: Index Number – should be Identification Number. In the google form you indicate this will be initials, date, and time, so would be useful to provide this information in the ethics form too • 6.3 iii) reviewed should read revealed (I think) • 6.3 iv) reword this point for clarity • 6.5 What is the end time for withdrawal (e.g. last date participants can withdraw before the report is written up) Independent Reviewer 2: Approved

You must discuss any untoward incident, during this project, which results in the completion of an accident claim form in the first instance to your supervisor as a matter of urgency and then via SST.ethics@ntu.ac.uk.

If you have any queries please do not hesitate to contact your project supervisor or alternatively e-mail SST.ethics@ntu.ac.uk.

Appendix C – SEM Experiment Result on the Inter-relationship of BDA and EA for Cs

value.R

N0643847

2023-05-07

```
library(lavaan) # Comprehensive package for SEM

## This is lavaan 0.6-15
## lavaan is FREE software! Please report any bugs.

library(MVN) # Package for assessing multivariate normality
library(semTools) # Suite of additional tools for SEM.

##

## ###############################################################
################

## This is semTools 0.5-6

## All users of R (or SEM) are invited to submit functions or ideas for functions.

## ###############################################################
################

library(readxl)
library(zoo)

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

library (semPlot)
library("openxlsx")
setwd("C:/Users/N0643847/Desktop")
SEM_data <- readWorkbook("survey_responses2_sln.xlsx", sheet = "survey_responses2", colNa
mes = TRUE)
multi <- mvn(SEM_data[,6:44], mvnTest = "mardia") # apply mvn() function to scores from questi
onnaire items
multi$multivariateNormality # display results of multivariate normality test

##             Test        Statistic              p value Result
## 1 Mardia Skewness 12764.7316066101 3.15764412256578e-42     NO
```

```
## 2 Mardia Kurtosis 6.67074320152454 2.54511967057169e-11     NO
## 3          MVN           <NA>              <NA>     NO

# STEP 1: specify the hypothetical measurement model
CFA_model <- '
BDA=~ data_volume + bdaTools_measure + value_creation + product_optimise
EA=~ customer_demand + newTech_adapt + quality_improvement + regPrice_review
PF=~ proft + market_growth + returns
CS=~ cust_feedback + prod_recommend + quality_improvement
'

# STEP 2: fit the model to the data
CFA_model_fit <- cfa(CFA_model, data = SEM_data, test = "bootstrap", se = "bootstrap", bootstra
p = 2000)

## Warning in lav_model_nvcov_bootstrap(lavmodel = lavmodel, lavsamplestats =
## lavsamplestats, : lavaan WARNING: 30 bootstrap runs failed or did not converge.

## Warning in lav_model_nvcov_bootstrap(lavmodel = lavmodel, lavsamplestats =
## lavsamplestats, : lavaan WARNING: 220 bootstrap runs resulted in nonadmissible
## solutions.

# STEP 3: evaluate goodness of fit
CFA_model_fit

## lavaan 0.6.15 ended normally after 63 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        33
##
##                                                   Used       Total
##   Number of observations                           118         125
##
## Model Test User Model:
##
##   Test statistic                               155.387
##   Degrees of freedom                                58
##   P-value (Chi-square)                           0.000
##
##   Test statistic                               155.387
##   Degrees of freedom                                58
##   P-value (Bollen-Stine bootstrap)               0.001

# STEP 3: evaluate goodness of fit
fitMeasures(CFA_model_fit, c("cfi", "gfi", "agfi", "rmsea"))

##   cfi   gfi  agfi rmsea
## 0.885 0.846 0.758 0.119

inspect(CFA_model_fit, what="std", na.rm = TRUE)$lambda # extract standardized factor loading
s from cfa model

##                     BDA    EA    PF    CS
## data_volume       0.604 0.000 0.000 0.000
## bdaTools_measure  0.796 0.000 0.000 0.000
```

```
## value_creation      0.587 0.000 0.000 0.000
## product_optimise    0.821 0.000 0.000 0.000
## customer_demand     0.000 0.576 0.000 0.000
## newTech_adapt       0.000 0.723 0.000 0.000
## quality_improvement 0.000 0.314 0.000 0.566
## regPrice_review     0.000 0.828 0.000 0.000
## proft               0.000 0.000 0.617 0.000
## market_growth       0.000 0.000 0.896 0.000
## returns             0.000 0.000 0.921 0.000
## cust_feedback       0.000 0.000 0.000 0.771
## prod_recommend      0.000 0.000 0.000 0.778
```

```
reliability(CFA_model_fit)# compute AVE and construct reliability
```

```
##              BDA        EA        PF        CS
## alpha  0.7789765 0.8166391 0.8382390 0.8386665
## omega  0.8021892 0.7741342 0.8509994 0.8071002
## omega2 0.8021892 0.5699124 0.8509994 0.6556613
## omega3 0.8207520 0.5755429 0.8572344 0.6558334
## avevar 0.5132179        NA 0.6597890        NA
```

```
#Specifying hypothesized model
mod1 <- '
BDA=~ data_volume + bdaTools_measure + value_creation + product_optimise
EA=~ customer_demand + newTech_adapt + quality_improvement + regPrice_review
PF=~ proft + market_growth + returns
CS=~ cust_feedback + prod_recommend + quality_improvement
'
mod2 <-'
BDA=~ data_volume + bdaTools_measure + value_creation + product_optimise
EA=~ customer_demand + newTech_adapt + regPrice_review
OP=~ proft + market_growth + returns + cust_feedback + prod_recommend + quality_improvem
ent
'
# fit models
fit1 <- cfa(mod1, data = SEM_data)
fit2 <- cfa(mod2, data = SEM_data)
# compare models with chi-square different test
anova(fit1, fit2)
```

```
##
## Chi-Squared Difference Test
##
##      Df    AIC    BIC  Chisq Chisq diff   RMSEA Df diff Pr(>Chisq)
## fit1 58 4953.4 5044.8 155.39
## fit2 62 5029.9 5110.3 239.91     84.522 0.41304       4  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# compare goodness-of-fit indices
fitMeasures(fit1, c("cfi", "gfi", "agfi", "rmsea"))
```

```
##   cfi   gfi  agfi rmsea
## 0.885 0.846 0.758 0.119
```

```
fitMeasures(fit2, c("cfi", "gfi", "agfi", "rmsea"))

##   cfi   gfi  agfi rmsea 
## 0.790 0.777 0.673 0.156

#Evaluating the full structural model

full_SEM <- '
BDA=~ data_volume + bdaTools_measure + value_creation + product_optimise
EA=~ customer_demand + newTech_adapt + quality_improvement + regPrice_review
PF=~ proft + market_growth + returns
CS=~ cust_feedback + prod_recommend + quality_improvement
#regrssion
PF~BDA+EA
EA~BDA
CS~PF
'

# STEP 2: fit the model to the data
SEM_model_fit <- sem(full_SEM, data = SEM_data)

SEM_model_fit

## lavaan 0.6.15 ended normally after 38 iterations
## 
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        31
## 
##                                                   Used       Total
##   Number of observations                           118         125
## 
## Model Test User Model:
##                                                       
##   Test statistic                               193.426
##   Degrees of freedom                                60
##   P-value (Chi-square)                           0.000

fit1 <- sem(full_SEM, data= SEM_data)
fit1

## lavaan 0.6.15 ended normally after 38 iterations
## 
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        31
## 
##                                                   Used       Total
##   Number of observations                           118         125
## 
## Model Test User Model:
##                                                       
##   Test statistic                               193.426
##   Degrees of freedom                                60
##   P-value (Chi-square)                           0.000
```

```
summary(fit1, standardized=TRUE)

## lavaan 0.6.15 ended normally after 38 iterations
##
##   Estimator                                         ML
##   Optimization method                               NLMINB
##   Number of model parameters                        31
##
##                                                   Used       Total
##   Number of observations                            118        125
##
## Model Test User Model:
##
##   Test statistic                                193.426
##   Degrees of freedom                                 60
##   P-value (Chi-square)                            0.000
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   BDA =~
##     data_volume       1.000                               1.086    0.607
##     bdaTools_measr    1.286    0.202    6.352    0.000    1.397    0.789
##     value_creation    0.753    0.146    5.158    0.000    0.818    0.583
##     product_optims    1.250    0.193    6.487    0.000    1.358    0.827
##   EA =~
##     customer_demnd    1.000                               0.890    0.584
##     newTech_adapt     1.274    0.214    5.955    0.000    1.134    0.741
##     qualty_mprvmnt    0.726    0.159    4.578    0.000    0.646    0.443
##     regPrice_reviw    1.365    0.218    6.262    0.000    1.215    0.813
##   PF =~
##     proft             1.000                               0.952    0.634
##     market_growth     1.332    0.174    7.675    0.000    1.268    0.890
##     returns           1.281    0.166    7.739    0.000    1.219    0.909
##   CS =~
##     cust_feedback     1.000                               1.089    0.723
##     prod_recommend    1.136    0.157    7.254    0.000    1.237    0.830
##     qualty_mprvmnt    0.739    0.127    5.828    0.000    0.804    0.552
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   PF ~
##     BDA              -0.195    0.161   -1.209    0.227   -0.222   -0.222
##     EA                0.927    0.255    3.636    0.000    0.867    0.867
##   EA ~
##     BDA               0.623    0.135    4.614    0.000    0.761    0.761
##   CS ~
##     PF                0.711    0.149    4.764    0.000    0.621    0.621
##
```

```
## Variances:
##                Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   .data_volume      2.026    0.294    6.890    0.000    2.026    0.632
##   .bdaTools_measr    1.180    0.222    5.321    0.000    1.180    0.377
##   .value_creation    1.298    0.186    6.984    0.000    1.298    0.660
##   .product_optims    0.855    0.184    4.649    0.000    0.855    0.317
##   .customer_demnd    1.530    0.217    7.040    0.000    1.530    0.659
##   .newTech_adapt    1.053    0.172    6.126    0.000    1.053    0.450
##   .qualty_mprvmnt    0.611    0.113    5.389    0.000    0.611    0.288
##   .regPrice_reviw    0.757    0.147    5.144    0.000    0.757    0.339
##   .proft           1.347    0.188    7.171    0.000    1.347    0.598
##   .market_growth    0.424    0.099    4.260    0.000    0.424    0.209
##   .returns         0.313    0.086    3.634    0.000    0.313    0.174
##   .cust_feedback    1.083    0.188    5.754    0.000    1.083    0.477
##   .prod_recommend    0.693    0.180    3.859    0.000    0.693    0.312
##    BDA             1.180    0.349    3.385    0.001    1.000    1.000
##   .EA              0.333    0.119    2.798    0.005    0.421    0.421
##   .PF              0.446    0.139    3.198    0.001    0.493    0.493
##   .CS              0.729    0.193    3.782    0.000    0.614    0.614
```

```
modindices(fit1, sort. = TRUE)
```

```
##                  lhs op               rhs     mi    epc sepc.lv sepc.all
## 146      market_growth ~~           returns 36.955  0.969   0.969    2.659
## 161                CS  ~                EA 30.496  1.006   0.822    0.822
## 158                PF  ~                CS 29.958 -0.890  -1.019   -1.019
## 157                PF ~~                CS 29.958 -0.649  -1.138   -1.138
## 165               BDA  ~                CS 18.065  0.761   0.763    0.763
## 154               BDA ~~                CS 18.065  0.554   0.598    0.598
## 162                CS  ~               BDA 18.065  0.470   0.469    0.469
## 52                 EA =~      cust_feedback 16.311  0.710   0.632    0.419
## 43                BDA =~      cust_feedback 15.683  0.469   0.510    0.338
## 71                 CS =~              proft 15.018  0.611   0.665    0.443
## 107    product_optimise ~~    customer_demand 14.917  0.521   0.521    0.455
## 56                 PF =~     value_creation 14.710  0.543   0.517    0.369
## 47                 EA =~     value_creation 13.129  0.923   0.822    0.586
## 70                 CS =~    regPrice_review 11.868  0.425   0.463    0.310
## 66                 CS =~     value_creation 11.735  0.404   0.440    0.313
## 75        data_volume ~~     value_creation 10.918 -0.558  -0.558   -0.344
## 36                BDA =~    customer_demand  9.927  0.720   0.782    0.513
## 72                 CS =~      market_growth  7.014 -0.322  -0.351   -0.246
## 73                 CS =~            returns  6.876 -0.302  -0.328   -0.245
## 74        data_volume ~~   bdaTools_measure  6.675  0.514   0.514    0.333
## 99      value_creation ~~      newTech_adapt  6.168  0.308   0.308    0.263
## 57                 PF =~   product_optimise  5.842 -0.364  -0.347   -0.211
## 122    customer_demand ~~      cust_feedback  5.619  0.324   0.324    0.252
## 46                 EA =~   bdaTools_measure  5.420 -0.739  -0.658   -0.372
## 88    bdaTools_measure ~~    customer_demand  4.704 -0.325  -0.325   -0.242
## 92    bdaTools_measure ~~              proft  4.587  0.295   0.295    0.234
## 42                BDA =~            returns  4.432 -0.187  -0.203   -0.151
## 118    customer_demand ~~    regPrice_review  4.421 -0.288  -0.288   -0.267
## 89    bdaTools_measure ~~      newTech_adapt  4.210 -0.275  -0.275   -0.246
## 141    regPrice_review ~~     prod_recommend  3.968  0.201   0.201    0.278
## 106     value_creation ~~     prod_recommend  3.965  0.230   0.230    0.242
```

```
## 98      value_creation ~~    customer_demand  3.916  0.278   0.278    0.197
## 76        data_volume ~~    product_optimise  3.834 -0.366  -0.366   -0.278
## 51                EA =~           returns  3.781 -0.315  -0.280   -0.209
## 150           returns ~~     prod_recommend  3.773 -0.144  -0.144   -0.310
## 160               EA  ~                CS  3.706  0.268   0.328    0.328
## 156               EA ~~                CS  3.706  0.195   0.396    0.396
## 124     newTech_adapt ~~ quality_improvement  3.350 -0.186  -0.186   -0.232
## 45                EA =~        data_volume  3.241  0.580   0.516    0.288
## 128     newTech_adapt ~~           returns  3.052  0.137   0.137    0.238
## 145             proft ~~     prod_recommend  3.025  0.203   0.203    0.210
## 101     value_creation ~~    regPrice_review  2.787 -0.188  -0.188   -0.190
## 48                EA =~    product_optimise  2.760 -0.503  -0.447   -0.272
## 147     market_growth ~~      cust_feedback  2.733 -0.142  -0.142   -0.210
## 111   product_optimise ~~             proft  2.708 -0.203  -0.203   -0.189
## 139    regPrice_review ~~           returns  2.695 -0.118  -0.118   -0.243
## 131 quality_improvement ~~    regPrice_review  2.688  0.161   0.161    0.237
## 87    bdaTools_measure ~~   product_optimise  2.682  0.363   0.363    0.362
## 50                EA =~      market_growth  2.491 -0.269  -0.239   -0.168
## 125     newTech_adapt ~~    regPrice_review  2.438  0.231   0.231    0.259
## 127     newTech_adapt ~~      market_growth  2.331 -0.129  -0.129   -0.193
## 94    bdaTools_measure ~~           returns  2.197 -0.126  -0.126   -0.207
## 143             proft ~~           returns  2.088 -0.149  -0.149   -0.230
## 82        data_volume ~~      market_growth  2.066 -0.157  -0.157   -0.170
## 83        data_volume ~~           returns  2.055  0.144   0.144    0.181
## 86    bdaTools_measure ~~     value_creation  2.021 -0.221  -0.221   -0.179
## 67                CS =~   product_optimise  2.016 -0.166  -0.181   -0.110
## 119    customer_demand ~~             proft  1.975 -0.199  -0.199   -0.139
## 144             proft ~~      cust_feedback  1.969  0.179   0.179    0.148
## 137    regPrice_review ~~             proft  1.889  0.155   0.155    0.153
## 39               BDA =~    regPrice_review  1.870 -0.298  -0.324   -0.217
## 58                PF =~    customer_demand  1.821 -0.288  -0.274   -0.180
## 40               BDA =~             proft  1.810  0.172   0.187    0.124
## 80        data_volume ~~    regPrice_review  1.736  0.187   0.187    0.151
## 49                EA =~             proft  1.711  0.276   0.245    0.163
## 95    bdaTools_measure ~~      cust_feedback  1.702  0.173   0.173    0.153
## 129     newTech_adapt ~~      cust_feedback  1.695  0.157   0.157    0.147
## 97     value_creation ~~   product_optimise  1.572  0.183   0.183    0.174
## 102     value_creation ~~             proft  1.482  0.159   0.159    0.120
## 110   product_optimise ~~    regPrice_review  1.391 -0.133  -0.133   -0.165
## 103     value_creation ~~      market_growth  1.390  0.103   0.103    0.138
## 142             proft ~~      market_growth  1.376 -0.127  -0.127   -0.169
## 37               BDA =~      newTech_adapt  1.361 -0.255  -0.277   -0.181
## 53                EA =~     prod_recommend  1.296  0.201   0.179    0.120
## 135 quality_improvement ~~      cust_feedback  1.138 -0.157  -0.157   -0.193
## 63                PF =~     prod_recommend  1.138 -0.236  -0.224   -0.150
## 108   product_optimise ~~      newTech_adapt  0.981 -0.120  -0.120   -0.127
## 116    customer_demand ~~      newTech_adapt  0.934  0.138   0.138    0.108
## 117    customer_demand ~~ quality_improvement  0.801 -0.099  -0.099   -0.102
## 85        data_volume ~~     prod_recommend  0.740 -0.125  -0.125   -0.105
## 136 quality_improvement ~~     prod_recommend  0.736  0.148   0.148    0.227
## 62                PF =~      cust_feedback  0.736  0.172   0.163    0.108
## 93    bdaTools_measure ~~      market_growth  0.698  0.077   0.077    0.109
## 115   product_optimise ~~     prod_recommend  0.681 -0.090  -0.090   -0.117
## 132 quality_improvement ~~             proft  0.618  0.078   0.078    0.086
```

```
## 96    bdaTools_measure ~~     prod_recommend  0.580 -0.093  -0.093   -0.102
## 100     value_creation ~~ quality_improvement  0.575 -0.075  -0.075   -0.084
## 78        data_volume ~~      newTech_adapt  0.485  0.108   0.108    0.074
## 113   product_optimise ~~           returns  0.442 -0.051  -0.051   -0.098
## 54                PF =~        data_volume  0.423  0.116   0.111    0.062
## 114   product_optimise ~~      cust_feedback  0.383  0.074   0.074    0.077
## 126     newTech_adapt ~~             proft  0.327 -0.071  -0.071   -0.060
## 79        data_volume ~~ quality_improvement  0.296  0.067   0.067    0.061
## 41               BDA =~      market_growth  0.278 -0.050  -0.054   -0.038
## 130     newTech_adapt ~~     prod_recommend  0.276  0.058   0.058    0.068
## 55                PF =~   bdaTools_measure  0.250 -0.081  -0.077   -0.044
## 121    customer_demand ~~           returns  0.236 -0.043  -0.043   -0.062
## 69                CS =~      newTech_adapt  0.212  0.061   0.066    0.043
## 148     market_growth ~~     prod_recommend  0.211 -0.037  -0.037   -0.068
## 138    regPrice_review ~~      market_growth  0.180 -0.033  -0.033   -0.058
## 61                PF =~    regPrice_review  0.162  0.083   0.079    0.053
## 59                PF =~      newTech_adapt  0.159  0.082   0.078    0.051
## 81        data_volume ~~             proft  0.151 -0.064  -0.064   -0.039
## 133 quality_improvement ~~      market_growth  0.150 -0.027  -0.027   -0.052
## 149           returns ~~      cust_feedback  0.137 -0.029  -0.029   -0.050
## 38               BDA =~ quality_improvement  0.133  0.061   0.067    0.046
## 104     value_creation ~~           returns  0.131 -0.029  -0.029   -0.045
## 68                CS =~    customer_demand  0.120  0.050   0.054    0.036
## 44               BDA =~     prod_recommend  0.118  0.039   0.042    0.028
## 60                PF =~ quality_improvement  0.092  0.057   0.054    0.037
## 151      cust_feedback ~~     prod_recommend  0.092  0.090   0.090    0.104
## 109   product_optimise ~~ quality_improvement  0.091  0.029   0.029    0.040
## 77        data_volume ~~    customer_demand  0.082 -0.050  -0.050   -0.029
## 134 quality_improvement ~~           returns  0.069  0.017   0.017    0.038
## 91    bdaTools_measure ~~    regPrice_review  0.065  0.031   0.031    0.033
## 90    bdaTools_measure ~~ quality_improvement  0.048  0.023   0.023    0.027
## 123    customer_demand ~~     prod_recommend  0.043 -0.026  -0.026   -0.025
## 140    regPrice_review ~~      cust_feedback  0.036  0.021   0.021    0.023
## 120    customer_demand ~~      market_growth  0.023  0.015   0.015    0.018
## 84        data_volume ~~      cust_feedback  0.023  0.024   0.024    0.016
## 65                CS =~   bdaTools_measure  0.013  0.015   0.016    0.009
## 64                CS =~        data_volume  0.012  0.016   0.017    0.010
## 105     value_creation ~~      cust_feedback  0.003 -0.007  -0.007   -0.006
## 112   product_optimise ~~      market_growth  0.002  0.004   0.004    0.006
##     sepc.nox
## 146    2.659
## 161    0.822
## 158   -1.019
## 157   -1.138
## 165    0.763
## 154    0.598
## 162    0.469
## 52     0.419
## 43     0.338
## 71     0.443
## 107    0.455
## 56     0.369
## 47     0.586
## 70     0.310
```

```
## 66    0.313
## 75   -0.344
## 36    0.513
## 72   -0.246
## 73   -0.245
## 74    0.333
## 99    0.263
## 57   -0.211
## 122   0.252
## 46   -0.372
## 88   -0.242
## 92    0.234
## 42   -0.151
## 118  -0.267
## 89   -0.246
## 141   0.278
## 106   0.242
## 98    0.197
## 76   -0.278
## 51   -0.209
## 150  -0.310
## 160   0.328
## 156   0.396
## 124  -0.232
## 45    0.288
## 128   0.238
## 145   0.210
## 101  -0.190
## 48   -0.272
## 147  -0.210
## 111  -0.189
## 139  -0.243
## 131   0.237
## 87    0.362
## 50   -0.168
## 125   0.259
## 127  -0.193
## 94   -0.207
## 143  -0.230
## 82   -0.170
## 83    0.181
## 86   -0.179
## 67   -0.110
## 119  -0.139
## 144   0.148
## 137   0.153
## 39   -0.217
## 58   -0.180
## 40    0.124
## 80    0.151
## 49    0.163
## 95    0.153
## 129   0.147
## 97    0.174
```

```
## 102    0.120
## 110   -0.165
## 103    0.138
## 142   -0.169
## 37    -0.181
## 53     0.120
## 135   -0.193
## 63    -0.150
## 108   -0.127
## 116    0.108
## 117   -0.102
## 85    -0.105
## 136    0.227
## 62     0.108
## 93     0.109
## 115   -0.117
## 132    0.086
## 96    -0.102
## 100   -0.084
## 78     0.074
## 113   -0.098
## 54     0.062
## 114    0.077
## 126   -0.060
## 79     0.061
## 41    -0.038
## 130    0.068
## 55    -0.044
## 121   -0.062
## 69     0.043
## 148   -0.068
## 138   -0.058
## 61     0.053
## 59     0.051
## 81    -0.039
## 133   -0.052
## 149   -0.050
## 38     0.046
## 104   -0.045
## 68     0.036
## 44     0.028
## 60     0.037
## 151    0.104
## 109    0.040
## 77    -0.029
## 134    0.038
## 91     0.033
## 90     0.027
## 123   -0.025
## 140    0.023
## 120    0.018
## 84     0.016
## 65     0.009
## 64     0.010
```

```
## 105   -0.006
## 112    0.006
```

```
inspect(fit1, what = "std")
```

```
## $lambda
##                     BDA    EA    PF    CS
## data_volume         0.607 0.000 0.000 0.000
## bdaTools_measure    0.789 0.000 0.000 0.000
## value_creation      0.583 0.000 0.000 0.000
## product_optimise    0.827 0.000 0.000 0.000
## customer_demand     0.000 0.584 0.000 0.000
## newTech_adapt       0.000 0.741 0.000 0.000
## quality_improvement 0.000 0.443 0.000 0.552
## regPrice_review     0.000 0.813 0.000 0.000
## proft               0.000 0.000 0.634 0.000
## market_growth       0.000 0.000 0.890 0.000
## returns             0.000 0.000 0.909 0.000
## cust_feedback       0.000 0.000 0.000 0.723
## prod_recommend      0.000 0.000 0.000 0.830
##
## $theta
##                     dt_vlm bdTls_ vl_crt prdct_ cstmr_ nwTch_ qlty_m rgPrc_
## data_volume         0.632
## bdaTools_measure    0.000  0.377
## value_creation      0.000  0.000  0.660
## product_optimise    0.000  0.000  0.000  0.317
## customer_demand     0.000  0.000  0.000  0.000  0.659
## newTech_adapt       0.000  0.000  0.000  0.000  0.000  0.450
## quality_improvement 0.000  0.000  0.000  0.000  0.000  0.000  0.288
## regPrice_review     0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.339
## proft               0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
## market_growth       0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
## returns             0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
## cust_feedback       0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
## prod_recommend      0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
##                     proft mrkt_g retrns cst_fd prd_rc
## data_volume
## bdaTools_measure
## value_creation
## product_optimise
## customer_demand
## newTech_adapt
## quality_improvement
## regPrice_review
## proft               0.598
## market_growth       0.000  0.209
## returns             0.000  0.000  0.174
## cust_feedback       0.000  0.000  0.000  0.477
## prod_recommend      0.000  0.000  0.000  0.000  0.312
##
## $psi
##     BDA    EA    PF    CS
## BDA 1.000
```

```
## EA  0.000 0.421
## PF  0.000 0.000 0.493
## CS  0.000 0.000 0.000 0.614
##
## $beta
##       BDA    EA    PF CS
## BDA  0.000 0.000 0.000  0
## EA   0.761 0.000 0.000  0
## PF  -0.222 0.867 0.000  0
## CS   0.000 0.000 0.621  0
```

```
##R square
inspect(fit1, 'r2')
```

```
##       data_volume    bdaTools_measure     value_creation    product_optimise
##            0.368             0.623             0.340             0.683
##    customer_demand      newTech_adapt quality_improvement     regPrice_review
##            0.341             0.550             0.712             0.661
##            proft      market_growth           returns      cust_feedback
##            0.402             0.791             0.826             0.523
##     prod_recommend                EA                PF                CS
##            0.688             0.579             0.507             0.386
```

```
fitmeasures(fit1)
```

```
##               npar               fmin              chisq
##             31.000              0.820            193.426
##                 df             pvalue     baseline.chisq
##             60.000              0.000            924.388
##        baseline.df    baseline.pvalue                cfi
##             78.000              0.000              0.842
##                tli               nnfi                rfi
##              0.795              0.795              0.728
##                nfi               pnfi                ifi
##              0.791              0.608              0.846
##                rni               logl  unrestricted.logl
##              0.842          -2462.718          -2366.005
##                aic                bic             ntotal
##           4987.436           5073.327            118.000
##               bic2              rmsea     rmsea.ci.lower
##           4975.329              0.137              0.116
##     rmsea.ci.upper     rmsea.ci.level       rmsea.pvalue
##              0.159              0.900              0.000
##     rmsea.close.h0 rmsea.notclose.pvalue    rmsea.notclose.h0
##              0.050              1.000              0.080
##                rmr         rmr_nomean               srmr
##              0.300              0.300              0.130
##       srmr_bentler  srmr_bentler_nomean               crmr
##              0.130              0.130              0.139
##        crmr_nomean         srmr_mplus  srmr_mplus_nomean
##              0.139              0.129              0.129
##              cn_05              cn_01                gfi
##             49.244             54.916              0.820
##               agfi               pgfi                mfi
##              0.726              0.540              0.568
```

```
##               ecvi
##              2.165
```

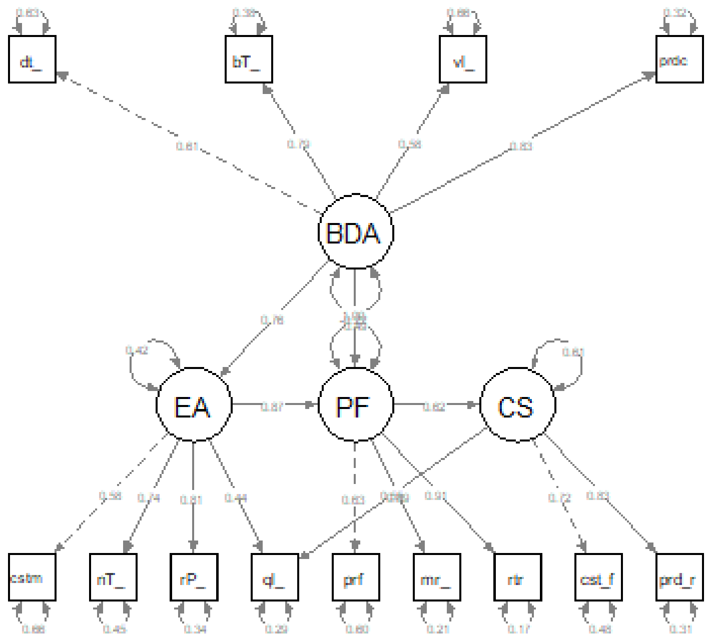
```
fitmeasures(fit1,c("gfi", "agfi", "nfi", "cfi", "rmsea", "srmr"))
```

```
##   gfi  agfi   nfi   cfi rmsea  srmr
## 0.820 0.726 0.791 0.842 0.137 0.130
```

```
fitMeasures(fit1, c("cfi", "rmsea", "srmr"))
```

```
##   cfi rmsea  srmr
## 0.842 0.137 0.130
```

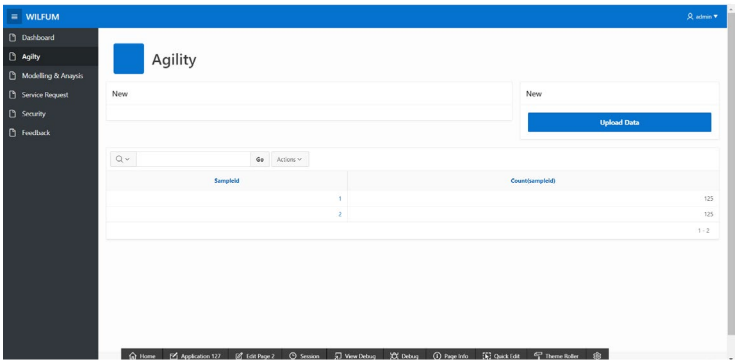
```
semPaths(fit1,what="paths", whatLabels = "stand", rotation=1)
```



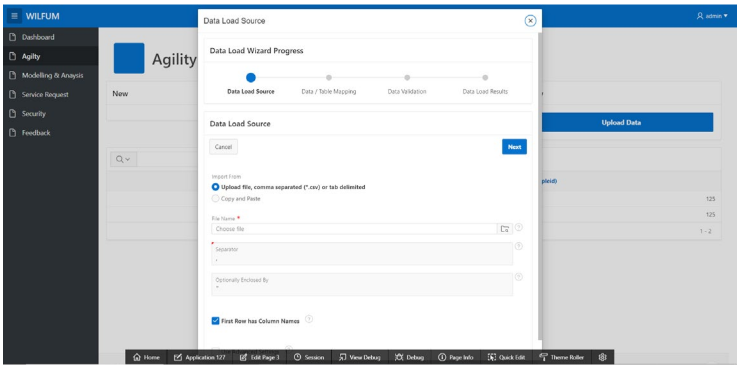
Appendix D – WILFUM Application

i. Illustration of Steps involved in calculating Enterprise Agility

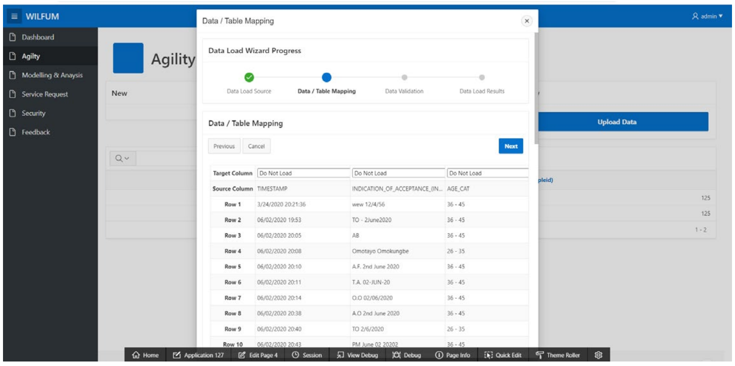
1. Agility main page illustrating the data upload details.



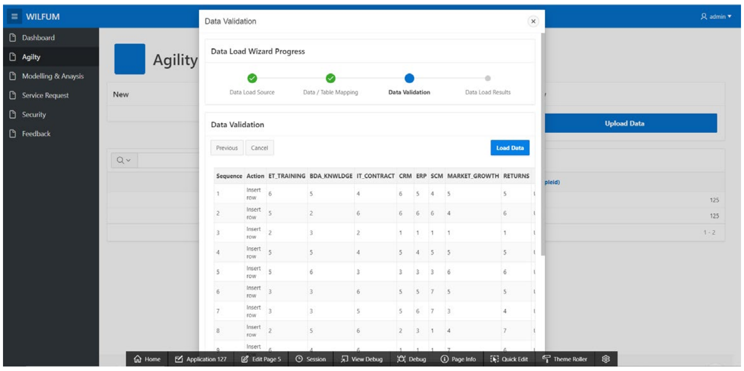
2. Data load wizard page. This is where the data can be uploaded in csv format or copied and pasted.



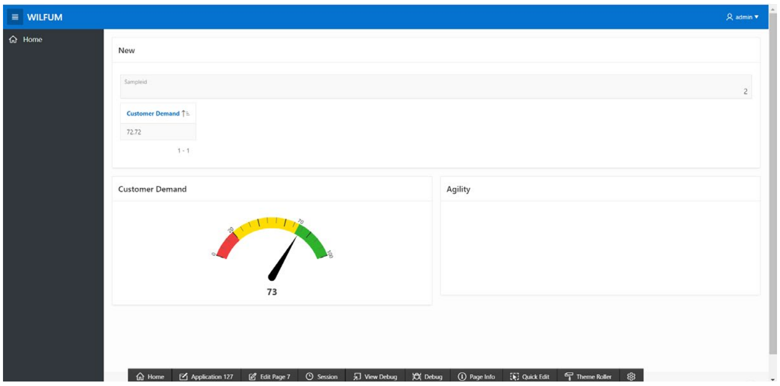
3. Data Mapping- Each data column must be mapped correctly before validation.



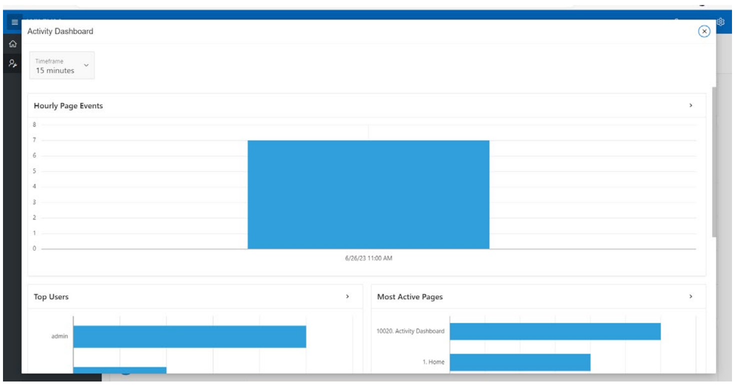
4. Data Validation ensures that the data to be used is accurate



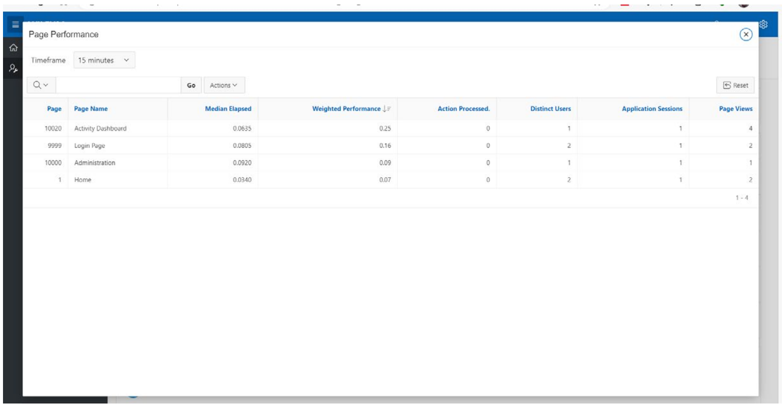
5. Data Results



ii. Reports Analytics in WILFUM dashboard application



a. Dashboard Metrics



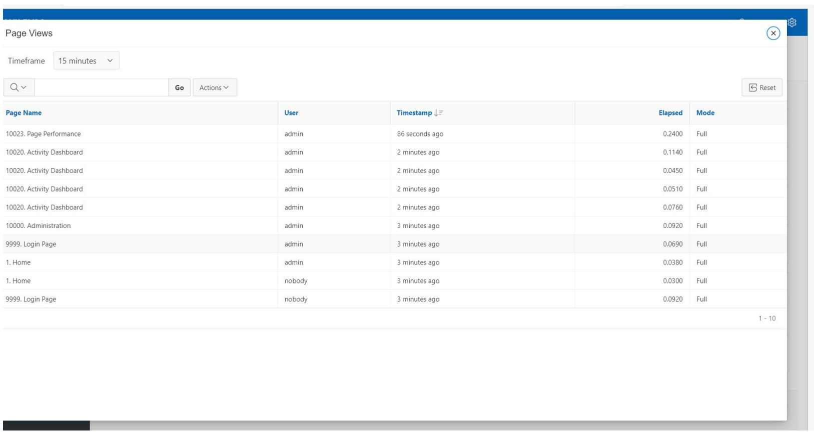
Page Performance

Timeframe 15 minutes

Page	Page Name	Median Elapsed	Weighted Performance	Action Processed.	Distinct Users	Application Sessions	Page Views
10020	Activity Dashboard	0.0635	0.25	0	1	1	4
9999	Login Page	0.0805	0.16	0	2	1	2
10000	Administration	0.0920	0.09	0	1	1	1
1	Home	0.0340	0.07	0	2	1	2

1 - 4

b. Page Performance



Page Views

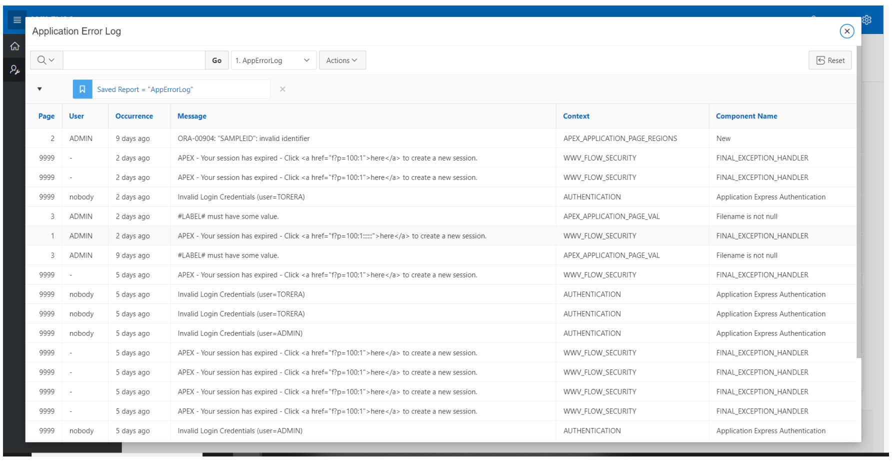
Timeframe 15 minutes

Page Name	User	Timestamp	Elapsed	Mode
10023. Page Performance	admin	86 seconds ago	0.2400	Full
10020. Activity Dashboard	admin	2 minutes ago	0.1140	Full
10020. Activity Dashboard	admin	2 minutes ago	0.0450	Full
10020. Activity Dashboard	admin	2 minutes ago	0.0510	Full
10020. Activity Dashboard	admin	2 minutes ago	0.0760	Full
10000. Administration	admin	3 minutes ago	0.0920	Full
9999. Login Page	admin	3 minutes ago	0.0690	Full
1. Home	admin	3 minutes ago	0.0380	Full
1. Home	nobody	3 minutes ago	0.0300	Full
9999. Login Page	nobody	3 minutes ago	0.0920	Full

1 - 10

c. Page View

iii. Illustration of the application error log



Application Error Log

1. AppErrorLog

Saved Report = "AppErrorLog"

Page	User	Occurrence	Message	Context	Component Name
2	ADMIN	9 days ago	ORA-00904: "SAMPLEID": invalid identifier	APEX_APPLICATION_PAGE_REGIONS	New
9999	-	2 days ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	-	2 days ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	nobody	2 days ago	Invalid Login Credentials (user=TORERA)	AUTHENTICATION	Application Express Authentication
3	ADMIN	2 days ago	#LABEL# must have some value.	APEX_APPLICATION_PAGE_VAL	Filename is not null
1	ADMIN	2 days ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
3	ADMIN	9 days ago	#LABEL# must have some value.	APEX_APPLICATION_PAGE_VAL	Filename is not null
9999	-	5 days ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	nobody	5 days ago	Invalid Login Credentials (user=TORERA)	AUTHENTICATION	Application Express Authentication
9999	nobody	5 days ago	Invalid Login Credentials (user=TORERA)	AUTHENTICATION	Application Express Authentication
9999	nobody	5 days ago	Invalid Login Credentials (user=ADMIN)	AUTHENTICATION	Application Express Authentication
9999	-	5 days ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	-	5 days ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	-	5 days ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	-	5 days ago	APEX - Your session has expired - Click here to create a new session.	WWV_FLOW_SECURITY	FINAL_EXCEPTION_HANDLER
9999	nobody	5 days ago	Invalid Login Credentials (user=ADMIN)	AUTHENTICATION	Application Express Authentication

Appendix E – Survey Questionnaire and Sample Application for Analytics

1. Survey Questionnaires for Research Study

Study on Analyzing the Impacts of Emergent Technology on Enterprise Agility, Using System Dynamics Modelling

Invitation
Before you decide to take part in this study it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully:
Purpose of Study
This research is conducted for my PhD thesis at Nottingham Trent University. Research aims to design dynamic model by utilizing the advantages of big data analytics in achieving agile and efficient business operations for benefits of organisations performance, in a turbulent technological environment. Using quantitative analysis under positivist paradigm, organisational system with an appropriate implementation of Big Data Analytics approach will be considered for the dynamic model and simulation. This research work will assist in predicting future business analysis towards enterprise agility for competitive advantages.

This study is totally voluntary, and every information and data provided would be kept anonymous and confidential throughout the entire study according to the GDPR of the United Kingdom.
This questionnaire has been divided into three sections.

Section 1: Professional Profile
Section 2: Organizational Value and Culture
Section 3: Big Data Analytics and its various contributions to your organisation based on participants view.

Note: Estimated Time for Completion is 20 minutes. For further inquiries, kindly send an email to the following address N0643847@my.ntu.ac.uk

Thank you for your contribution as it is important and highly appreciated.

Term Used for Clarification
Enterprise Agility (EA) – It is the ability of an organisation to detect unexpected changes and respond rapidly to changes by satisfying customers' demands. EA measures on productivity performances of an organisation whilst reducing cost, for value creation, by re-configuring their resources to perform beyond expectation in both levels of effectiveness and efficiency.

BDA - Big Data Analytics, FP – Firms Performance, EA – Enterprise Agility

Investigator

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* Indicates required question

Participant Consent Form

i. I confirm that I have read and understood the Participant Information Sheet.
ii. I am above the age of 18 and consent voluntarily to be a participant in this study.
iii. I understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.
iv. In the event of withdrawal of participation, Kindly contact the lead researcher via email on N0643847@my.ntu.ac.uk indicating your request, and stating initials used, date and time of completion of the form.
v. I understand that taking part in the study requires me to provide data and that this will involve completing an online questionnaire.

Jse of my data in the study
. I understand that data which can identify me will not be shared beyond the project team.
i. I agree that any data that I provide may be used for the following: Presentation and discussion of the project and its results in research activities (e.g. project meetings, conferences). Publications and reports describing the project and its results on web-pages and databases
ii. I agree that data gathered in this study may be stored anonymously and securely with the university's data bank and must
be destroyed 6 months after the project completion.
v. I agree to take part in this study.

1. Indication of Acceptance (Initials only and Date) *

Section 1: Professional Profile

This section considers participant's demography

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2. What age group category do you fall under?

Mark only one oval.

- 18 - 25
- 26 - 35
- 36 - 45
- 46 - 55
- 56 - 65
- Above 65

3. What is your current position / level in your job?

4. Please Select your highest educational level

Mark only one oval.

- High School
- A-Levels
- College Graduate
- Undergraduate degree
- Masters
- Doctorate
- Other:

5. 4. Using a scale of 1 -7 where 1 is Strongly low and 7 is strongly high, rate your knowledge on Enterprise Agility

Mark only one oval.

	1	2	3	4	5	6	7	
Stro								Strongly High

6. 4. Using a scale of 1 -7 where 1 is Strongly low and 7 is strongly high, rate your knowledge on Emergent Technology (e.g. Big data analytics, Machine learning, Artificial Intelligence, etc.)

Mark only one oval.

	1	2	3	4	5	6	7	
Stro								Strongly High

Section 2: Organizational Value and Culture

This section looks at knowledge (both technical and organisational) in your organisations as well as how much effort is used for development of persons for value creation.

1. Technical and Managerial Skills (Human Skills and Development)
Using the scale of 1- least Likely to 7-Very Likely, please answer the following questions

7. To what extent do persons get to be trained on emerging technology?

Mark only one oval.

	1	2	3	4	5	6	7	
Leas								Very Likely

8. Based on your level of knowledge, how knowledgeable are IT persons and you on Big Data Analytics?

Mark only one oval.

	1	2	3	4	5	6	7	
No I								Very Knowledgeable

9. To what extent are you competent in the area of data management and maintenance of data?

Mark only one oval.

1 2 3 4 5 6 7

Leas ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very Competent

10. How proficient are you in the use of decision support systems (e.g. artificial intelligence, machine learning, predictive analysis, etc.)?

Mark only one oval.

1 2 3 4 5 6 7

Lea: ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very Proficient

11. How often does your organisation contract IT related issues to external contractors?

Mark only one oval.

1 2 3 4 5 6 7

Lea: ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very Often

12. Whats your level of capability on the management of support systems and project life cycle?

Mark only one oval.

1 2 3 4 5 6 7

Littl ◯ ◯ ◯ ◯ ◯ ◯ ◯ Strong Capability

2. Organisational Knowledge

Using the 7 point-Likert scale with 1- no knowledge / least likely and 7- strong knowledge/very likely, please answer the following questions:

13. How familiar are you with your organisations vision and Policies?

Mark only one oval.

1 2 3 4 5 6 7

Not ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very familiar

14. How knowledgeable are you with the factors that enables success for your organisation?

Mark only one oval.

1 2 3 4 5 6 7

No I ◯ ◯ ◯ ◯ ◯ ◯ ◯ Strong Knowledge

15. To what extent are your familiar with the business application platforms used in your organisation?

Mark only one oval.

1 2 3 4 5 6 7

Not ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very Familiar

16. How familiar are you with the technological maintenance culture of your organisation?

Mark only one oval.

1 2 3 4 5 6 7

Not ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very Familiar

17. How familiar are you with the Key Performance Index of your organisation?

Mark only one oval.

1 2 3 4 5 6 7

Not ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very Familiar

18. How often is the KPI of your organisation measured?

Mark only one oval.

1 2 3 4 5 6 7

Not ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very Often

3. IT Management

Using the 7-Point Likert scale with 1 - Not Often and 7 - Very Often, please answer the following questions on Information Technology (IT) management of your organisation.

19. How often does the management team meet with other staff members?

Mark only one oval.

1 2 3 4 5 6 7

Not ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very Often

20. How often are analytical performances measured?

Mark only one oval.

1 2 3 4 5 6 7

Not ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very Often

21. How often are decisions made with the input of other staff members?

Mark only one oval.

1 2 3 4 5 6 7

Not ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very Often

Section 3: Big Data Analytics (BDA) and its contribution towards organisational agility and performance

1. BDA Capabilities

This following set of questions is required to measure the the capability of your organisation with respect to big data analytics

22. How often does your organisation produce large volume of data?

Mark only one oval.

1 2 3 4 5 6 7

Not ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very Often

23. To what extent does your organisation use BDA tools? e.g. Hadoop, Apache spark, etc.

Mark only one oval.

1 2 3 4 5 6 7

Not ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very Often

To what extent has your organisation enforce the use of BDA on the following platforms listed below:

Usinf the scale of 1 - Least Likely and 7 - Very Likely, Please answer the following

24. Customer Relationship Management (CRM)

Mark only one oval.

	1	2	3	4	5	6	7	
Lea:	◯	◯	◯	◯	◯	◯	◯	Very Likely

25. Enterprise Resource Planning (ERP)

Mark only one oval.

	1	2	3	4	5	6	7	
Lea:	◯	◯	◯	◯	◯	◯	◯	Very Likely

26. Predicting and Demand Management

Mark only one oval.

	1	2	3	4	5	6	7	
Lea:	◯	◯	◯	◯	◯	◯	◯	Very Likely

27. Sourcing Analysis

Mark only one oval.

	1	2	3	4	5	6	7	
Lea:	◯	◯	◯	◯	◯	◯	◯	Very Likely

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28. Supply Chain Management

Mark only one oval.

	1	2	3	4	5	6	7	
Lea:	◯	◯	◯	◯	◯	◯	◯	Very Likely

29. Production Optimization

Mark only one oval.

	1	2	3	4	5	6	7	
Lea:	◯	◯	◯	◯	◯	◯	◯	Very Likely

30. Value Creation

Mark only one oval.

	1	2	3	4	5	6	7	
Lea:	◯	◯	◯	◯	◯	◯	◯	Very Likely

2. Enterprise Agility

The following questions are designed to measure the agility of your organisation

31. How often does your organisation respond to customers' demands?

Mark only one oval.

	1	2	3	4	5	6	7	
Not	◯	◯	◯	◯	◯	◯	◯	Very Often

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32. How fast does your organisation adapts and utilize new technology?

Mark only one oval.

	1	2	3	4	5	6	7	
Very	◯	◯	◯	◯	◯	◯	◯	Very Fast

33. How often does your organisation review prices for regulation in response to its competitors?

Mark only one oval.

	1	2	3	4	5	6	7	
Lea:	◯	◯	◯	◯	◯	◯	◯	Very Often

34. How often are stakeholders and suppliers contacted for quality improvement and for efficiency monitoring?

Mark only one oval.

	1	2	3	4	5	6	7	
Lea:	◯	◯	◯	◯	◯	◯	◯	Very Often

Environmental Turbulence (Technological and Market Changes)

35. How often do customers recommend your products?

Mark only one oval.

	1	2	3	4	5	6	7	
Lea:	◯	◯	◯	◯	◯	◯	◯	Very Often

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36. How often are feedback from customers reviewed and acted upon?

Mark only one oval.

	1	2	3	4	5	6	7	
Lea:	◯	◯	◯	◯	◯	◯	◯	Very Often

37. How often does your organisation adopt technological changes for market breakthrough?

Mark only one oval.

	1	2	3	4	5	6	7	
Lea:	◯	◯	◯	◯	◯	◯	◯	Very Often

38. With the effect of social media, rate the breakthrough of marketing services.

Mark only one oval.

	1	2	3	4	5	6	7	
No S	◯	◯	◯	◯	◯	◯	◯	High Significant Change

39. To what extent do you agree or disagree that the adoption of technology enables a more secured environment for the organisation

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

Organisational Performance

Over the last 2 years, the organisation has improved on the following:

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40. *Mark only one oval.*

- Option 1: Strongly disagree
- Option 2:

41. Profitability

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

42. Market growth

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

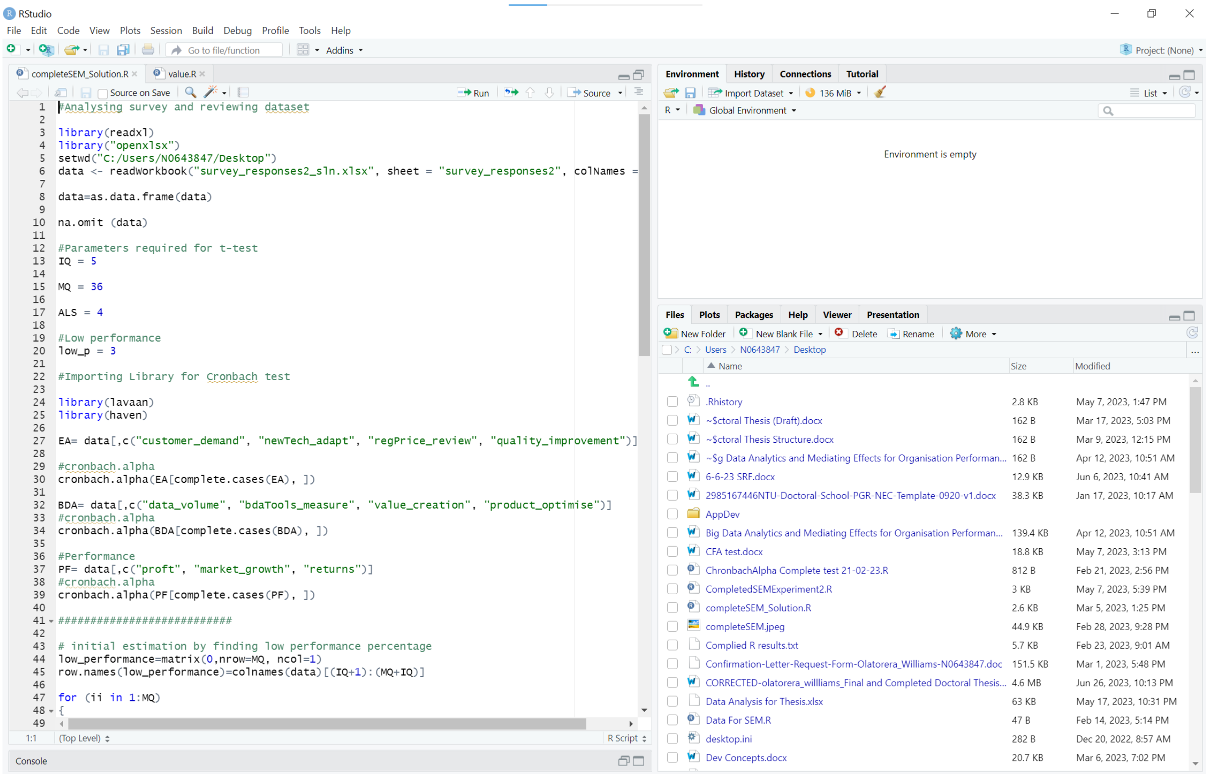
43. Returns

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

https://docs.google.com/forms/d/1x8c1ngoeVIODK5VHNlxZhpEoz7uNRMDwUOD4qHRjMdo/edit 13/14

2. Sample Application of R studio used in Analytics



Appendix F – Participant Consent Form and Participant Information Sheet

i. Participant Consent Form

NOTTINGHAM TRENT UNIVERSITY

SCHOOL OF SCIENCE AND TECHNOLOGY

Analysing the impacts of Emergent Technology on Enterprise Agility using System Dynamics Modelling

Participant Consent Form

i. I confirm that I have read and understand the Participant Information Sheet
ii. I have had the opportunity to ask questions and had them answered
iii. I understand that all personal information will remain confidential and that all efforts will be made to ensure I cannot be identified (except as might be required by law)
iv. I agree that data gathered in this study may be stored anonymously and securely, and may be used for future research
v. I understand that my participation is voluntary and that I am free to withdraw at any time without giving a reason.
vi. I agree to take part in this study

Participants Name:

Date:

ii. Participants Information Sheet

The PIS is given as follows:

NOTTINGHAM TRENT UNIVERSITY

SCHOOL OF SCIENCE AND TECHNOLOGY

Analysing the impacts of Emergent Technology on Enterprise Agility using System Dynamics Modelling

Invitation

Before you decide to take part in this study it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully:

Purpose of Study

This research is conducted for my PhD thesis at Nottingham Trent University. The aims focus on the role of Big Data Analytics for Enterprise Agility whilst improving organization performance and adapting to changing environment, by reducing productivity cost and satisfying customers' needs. The outcome of the research work will be analysed and implemented into a system dynamic model for test simulations to be carried out for its applications. Further research work will be implemented for the creation of a framework to be developed. The research intentions are to utilize the result of the analysis and to be applied on a case study of business organisations. This is to measure and evaluate the process and performance improvement in product design, development and value creation for a lifetime advantages based on KPI in a competitive technological environment.

This study is totally voluntary, and every information and data provided would be kept anonymous and confidential throughout the entire study according to the GDPR of the United Kingdom.

This questionnaire has been divided into three parts.

Part 1: Professional Profile

Part 2: Organizational/Firms Culture and Structure

Part 3: Big Data Analytics and its various contributions to your organisation based on participants view.

Note: Estimated Time for Completion is 20 minutes. For further inquiries, kindly send an email to the following address N0643847@my.ntu.ac.uk

Thank you for your contribution as it is important and highly appreciated.

Term Used for Clarification

Enterprise Agility (EA) – It is the ability of a organisation to detect unexpected changes and respond rapidly to changes by satisfying customers' demands. EA measures on productivity performances of an organisation whilst reducing cost, for value creation, by reconfiguring their resources to perform

Appendix G – Feedback from Use-Case Service Organisation

1. Screenshot of Case study application

Dear Olatorera,

We would like to express our sincerest gratitude for the WilFum application you implemented for our organisation's usage.

The software application is of great help as we have been able to calculate our previous agility level from pre-covid (2018) till date April, 2023. This has enabled the change management team to take effective measures towards the company's development and within a few weeks of usage we are seeing a positive outcome.

Our IT team has also given feedback that the security aspect of the application is very useful. They now receive alerts based on potential threats such as invalidated login from user's and invalidated access alerts. Though all false positives, we are happy that every aspect of the application works according to its described functionalities and advantages..

Thank you once again for the development and we wish you success in your PhD program.

Best Regards,

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