AI for GBS: Experiences, Use Cases, and Implementation.

Leon Leander Kriegel
152122570

Dissertation written under the supervision of Professor René Bohnsack

Dissertation submitted in partial fulfilment of requirements for the MSc in Strategy, Entrepreneurship and Impact, at the Universidade Católica Portuguesa, 03.01.2024.

Abstract

English

The increasing integration of Artificial Intelligence into business processes has revolutionised the way organisations do business around the world. In an era where efficiency, agility and competitiveness are critical, GBS play an important role in the strategic management of companies. The efficiency and performance of GBS are central to meet the diverse demands of a global supply chain while remaining competitive. In this context, the implementation of AI into GBS will be analysed in collaboration with Nebula. The process-based integration of AI is highlighted on the examples of the H2R and the T&E process. Finally, an AI readiness assessment for GBS units is developed and applied to the context of Nebulas GBS using qualitative and explorative methods. AI offers the potential to significantly increase productivity and efficiency, reduce human error and optimise resource utilisation. But while the benefits are obvious, the challenges and hurdles to successfully implementing AI in GBS processes should not be underestimated.

Portuguese

A crescente integração da Inteligência Artificial nos processos empresariais revolucionou a forma como as organizações fazem negócios em todo o mundo. Numa era em que a eficiência, a agilidade e a competitividade são fundamentais, o GBS desempenha um papel importante na gestão estratégica das empresas. A eficiência e o desempenho do GBS são fundamentais para satisfazer as diversas exigências de uma cadeia de abastecimento global, mantendo-se competitivo. Neste contexto, a implementação de IA no GBS será analisada em colaboração com a Nebula. A integração de IA baseada em processos é destacada nos exemplos do processo de contratação até à reforma e do processo de viagens e despesas. Por último, é desenvolvida e aplicada ao contexto de Nebulas GBS uma avaliação ao grau de preparação de IA, utilizando métodos qualitativos e exploratórios. IA oferece o potencial para aumentar significativamente a produtividade e a eficiência, reduzir o erro humano e otimizar a utilização dos recursos. Mas, embora os benefícios sejam óbvios, os desafios e obstáculos à implementação bem-sucedida de IA nos processos de GBS não devem ser subestimados.

Keywords: Artificial Intelligence, Global Business Services, Robotic Process Automation, Digital Strategy

Acknowledgement

I would like to thank my professor René Bohnsack, my teaching assistants Cláudia Antunes Marante and Arash Rezazadeh as well as Nebula's thesis supervisor, who supported and mentored me throughout this dissertation. Thank you for always taking the time to answer my questions and for guiding me through the entire process. I would also like to thank my supportive environment, as well as everyone from Nebula who participated in my interviews.

Thanks to all of you!

Table of Abbreviation

TERM	ABBREVIATION
Artificial General Intelligence	AGI
Artificial Intelligence	AI
Artificial Narrow Intelligence	ANCI
Artificial Neural Network	ANN
Artificial Super Intelligence	ASI
Big Data	BD
Business Analytics	BA
Business Intelligence	BI
Business Process Outsourcing	BPO
Deep Learning	DL
Deep Neural Network	DNN
End-To-End	E2E
Enterprise Resource Planning	ERP
European Commission	EC
European Union	EU
General Data Protection Regulation	GDPR
Generative Adversarial Networks	GAN
Generative Artificial Intelligence	GenAI
Global Business Services	GBS
Hire-To-Retire	H2R
Human Resource Information System	HRIS
Human Resources	HR
Large Language Model	LLM
Machine Learning	ML
Manager For Transition	MFT
Natural Language Processing	NLP
Neural Network	NN
Optical Character Recognition	OCR
Robotic Desktop Automation	RDA
Robotic Process Automation	RPA
Shared Service Centre	SSC
Standard Operating Procedure	SOP
Travel And Expenses	T&E
Variational Autoencodes	VAE

Table of Contents

Table of Figures

Figures

Tables

1 Introduction

We are in the age of digital transformation, which has fundamentally changed global business processes (Hill, 2022). The continuous change of business processes and the ongoing digitalisation have led companies worldwide to develop innovative models to increase their efficiency and competitiveness (Kitsios & Kamariotou, 2021). In particular, the introduction of Global Business Services (GBS) as a central component of a digital business strategy is having an impact on the way companies organise their operational functions (Maslak et al., 2021; Russell et al., 2022; Wirtz et al., 2015).

In the context of these developments, the aim of this thesis is to provide an in-depth insight into the relationship between GBS and the latest advances in process automation technology. A particular focus is placed on analysing the influence of technological progress on the strategic orientation of GBS, with automation potential taking centre stage. Various technologies can be used for corresponding use cases. The currently prevailing trend of Artificial Intelligence (AI) has already been the subject of intensive research in the business world for several years to utilise it for its own competitiveness (Krakowski et al., 2023).

Parallel to the development of global business processes, AI has experienced exponential growth and transformation in recent years. According to the statistics of Statista (2023) and Forbes (2023), AI has quickly developed from a niche concept to a megatrend with crucial relevance in the business context. Within different research reports published in March 2023, there is a clear focus on how AI can unleash and thus redefine the automation potential in different departments of an organisation (McKinsey, 2023; Stanford University, 2022).

Before analysing AI use cases for GBS, it is important to understand the current state of development. The statistics on several topics such as corporate investment, global market for AI, data processing and cloud technologies and productivity gains risk due to AI play an important role (Stanford University, 2022). For example, corporate investment in AI increased more than sevenfold between 2015 and 2022 (Stanford University, 2023), and the global market for AI is expected to reach USD 1.85 trillion by 2030 (Next Move Strategy Consulting, 2023). Furthermore, the early use of Generative Artificial Intelligence (GenAI) is expected to lead to an increase of more than 15% in productivity by 2040 (McKinsey, 2023).

Media coverage further emphasises these statistics. Relevant trade journals and the management levels of some of the world's largest corporations are committed to adopt the emerging technology. "AI has been one of the most transformative technologies of the 21st century" (Economic Times, 2020), "AI is the most important invention of mankind" (Pichai, 2023), "The integration of AI into business processes can be seen as a turning point in the evolution of corporate commerce" (Endrizzi, 2023) are only three examples of this. However, it is also important to consider the risks associated with AI and the potential for job losses in certain sectors. Statistics show the risks are expected in the Eurozone (Goldman Sachs, 2023).

The focus of this thesis is to investigate the benefits and impacts of implementing AI in a Global Business Service (GBS) unit. For this purpose, this thesis was developed with the GBS unit of a company which is given the fictitious name "Nebula" hereinafter. Both the company and the interviewed experts were anonymised so as not to disclose any information from the company under investigation. The focus lays on the processes of Hire-to-Retire (H2R) and Travel and Expenses (T&E), as these are holistically owned by the GBS.

The aim of the work is to provide information on the correct use of AI, to show the current state of development, to recognise potential in the structures of Nebula GBS and to make appropriate recommendations. Furthermore, a blueprint is to be developed to help managers in GBS structures to classify their own use cases in order to use AI correctly in their environment.

A guideline through the thesis is described. It begins with the establishment of the literature review which navigates through knowledge of existing literature, contextualizing AI's applicability. Building upon this, the research methodology takes an explorative approach, employing qualitative methods to assess prior experiences, tools in use and brainstorm for optimization potentials and use cases. Afterwards, the thesis includes short discussion, navigating through the ethical and philosophical dimensions of AI in business, juxtaposed with the pragmatic business-oriented perspective. Finally, this thesis offers a broad review of AI's role within Nebula GBS, encapsulating its potential impact, challenges, and strategic recommendations. It is poised to provide valuable insights for businesses and policymakers as they navigate the evolving landscape of AI and GBS.

Furthermore, challenges and possible obstacles in the implementation of AI are analysed and concrete methods for strategic alignment are provided. Finally, this thesis will formulate clear and actionable recommendations aimed at sustainably increasing the efficiency and productivity of Nebula's GBS through the targeted use of AI. This thesis will focus on the European market, as it aligns closely with Nebula's strategic vision.

The following research questions (RQ) resulted from this research objective:

RQ1: How can the use of AI maximise growth potential and productivity at Nebula's GBS?

RQ2: Were has AI the largest impact in Nebula's GBS operations?

RQ3: Which impact will the implementation of AI into a GBS unit have on the way of working?

RQ4: What differentiates an AI implementation into a GBS unit from regular business?

2 Literature Review

2.1 Global Business Services

The GBS model traditionally entails centralising internal company processes, either in part or entirely, to internal or external company units, both domestically and internationally, with the goal of enhancing productivity (Wirtz et al., 2015). A GBS unit employs a variety of service models, including outsourcing, centres of excellence, or shared services, to achieve its objectives (Deloitte, 2021). As a cardinal constituent of a firm's digital approach (BCG, 2023), its dynamic structure provides considerable competitive advantages in optimisation (Hodge, 2020).

Technology support plays a crucial role in Business Process Outsourcing (BPO) (Ukor & Carpenter, 2012), as it provides organisations with the flexibility to adopt new technologies quickly and adapt quickly to changing market and business needs . Especially in the context of Business Analytics (BA) and knowledge process outsourcing, the use of technology comes into play to increase the efficiency and effectiveness of outsourced processes (Lacity et al., 2017). In addition, technology enables the automated creation of cross-organisational processes, facilitating the dynamic outsourcing of business processes (Grefen et al., 2009).

Traditionally, rather monotonous and repetitive process sections have been offshored to low-wage countries to achieve the original objective of cost reduction (Pradhan, 2017). This encompassed various back-office activities, including finance, human resources (HR), IT, procurement, and tax, as well as customer-facing tasks such as call centres and customer services (Cherbakov et al., 2005). The service profile of GBS has expanded to include many areas, including software development, with the help of emerging technologies. GBS units also exhibit greater flexibility and entrepreneurial agility in their approach, as they are not tied strictly to a business unit (Anand, 2022). Agility and flexibility are also emphasised by PwC (2021), which describe this aspect as the ability to implement things faster. This flexibility facilitates the delivery of bespoke solutions that are designed to meet the unique needs of clients (Wirtz & Ehret, 2009). The ongoing transformation in service provision is occasionally referred to as the subsequent phase or a new era of BPO (Gupta & Fersht, 2023).

The configurations of diverse GBSs diverge considerably in relation to organisation, hierarchy, and political elements. As there is no one-fits-all definition, *Table 1* endeavours to present a framework that explicates the evolution of BPO. This is based on various criteria, such as geography, culture, strategic focus, automation level, and other key categories. *Table 1* was developed based on Wirtz et al. (2015), Kakabadse and Kakabadse (2000), Piatanesi and

Arauzo-Carod (2019), Aron and Singh (2005), Bryan (2019), Gupta and Fersht (2023), BCG (2023) and McKinsey (2023).

	Shared Service Center			Global Business Services	
	Nearshoring	**Offshoring**	**Shared Service Centres**	**Global Business Services**	**Autonomous Business Service**
Definition	Nearshoring refers to the practice of outsourcing business processes or services to a nearby or relatively close geographic location, often in the same region or time zone.	Offshoring involves outsourcing business processes or services to a different country, typically one with lower labour costs.	Shared Service Center (SSC) are centralized units within an organization that consolidate specific functions or services to achieve efficiency and cost savings.	External GBS refers to outsourcing the management and execution of business support functions to an external service provider.	The term Autonomous Business Service/Generative Business Services is not a widely recognized industry term. It refers to a business service or function that operates independently with a high degree of automation and autonomy.
Purpose	Organizations opt for nearshoring to take advantage of cost savings while maintaining proximity for better communication and reduced cultural differences.	Offshoring aims to benefit from cost advantages while potentially accessing a larger talent pool. It may involve greater time zone differences and cultural distinctions.	SSCs aim to streamline processes, improve service quality, and reduce duplication of efforts by consolidating certain business functions.	GBS allows organizations to benefit from specialized expertise and resources without handling these services internally. They aims to enhance efficiency, standardize processes, and provide better support to business units	This GBS state leverages advanced technologies and automation to perform tasks without constant human intervention.
Location Independence	Proximity to the organization's location	Significant geographic separation	Internal to the organization	Internal/external to the organization	Internal/external (depending on server location)
Ownership and Controll	Internal ownership and control	Internal or external ownership	Internal ownership and control	Shared ownership	Owned autonomously (hosted at the Data Center)
Degree of Centralization	Varies, often centralized	Varies, often centralized	Centralized	Centralized	Centralized
Strategic Focus	Balance of cost savings and collaboration	Cost-effective global operations	Internal process optimization	Collaboratio for specialized services	High-tech; autonomous operations
Level of Automation	Moderate automation	Varies, often low to moderate	Moderate automation	Moderate to high automation	High automation and autonomy
Culture & Communication	Reduced cultural differences	Potential cultural challenges	Internal collaboration	Potential external collaboration challenges	Requires definition of the "corpus"
Flexibility & Adaptability	Moderate flexibility	Moderate flexibility	Moderate flexibility	Moderate flexibility	High flexibility & adaptability
Level of Specialization	Generalized services	Generalized to specialized services	Centralized specialized services	External specialized services	Specialized autonomous services
Potential to "work in Silos"	High potential	High potential	Moderate potential	Low potential	N/A
Human Capital Development	Low potential	Low potential	Moderate potential	High potential	N/A

Table 1 The evolution of BPO

Historically, firms have broadened their service scope by engaging in digital and service transformation (Kakabadse & Kakabadse, 2000), which led to the emergence of various forms of BPO such as nearsourcing, offsoring, Shared Service Centres (SSC), and GBSs (Töytäri et al., 2018). *Table 1* demonstrates the different structures, beginning from traditional outsourcing to the prospective outlook of automated business services. The different classifications of BPO share several similarities hhave been proven by Piatanesi & Arauzo-Carod (2019), Aron & Sign (2005), Bryan (2019). Nevertheless, upon comparing them to GBS structures, the differences become apparent. Based on Wirtz et al. (2015), *Table 1* illustrates significant differences in political affiliation, decision-making powers, service portfolio and organisational culture between outsourcing models.

Nearshoring is an approach that helps companies resolve the cost-risk vs distance dilemma by choosing locations that do not necessarily provide the biggest cost savings, but are associated with lower risks (Slepniov et al., 2013).

Offshoring involves running a portion of business operations in another country (Peatman, 2022) and is driven by the need to enhance the firms' competitive advantage by exploiting local talent and expertise in host organisations or economies (Pereira et al., 2019).

As Bryan (2019) illustrates, SSCs possess the unique attribute of being capable of providing support for specialised business units, like customer support operations. An SSC has a single or limited number of core operational tasks as its objective.

Representing the next step in the historical development of outsourcing, GBSs characteristic differ from simpler outsourcing structures. GBS can be considered as a fusion of various BPO types (Deloitte, 2021). Due to its centralisation, this amalgamation can monitor the performance of the whole business unit more effortlessly while coordination may be severely hampered if managed independently by individual SSCs (Sagawa, 2022).

Literature describes Autonomous Business Services or Generative Business services as the next development step prognosed after GBS, whereby naming referred to GenAI. This state is described by Gupta & Fersht (2023) and Reyes (2021) as a data-based approach of decision-making and process automation where intelligent solutions play a substantial role throughout all GBS activities.

The current transformation trend with GBS remains. In recent years, it has become apparent that GBS transformation not only enables cost reduction and increased efficiency, but it also encompasses a wider range of business success (Bendor-Samuel, 2023). These new activities include piloting IT projects, creating knowledge repositories for the company and enhancing company-wide compliance (Gupta & Fersht, 2023).

GBS studies from recent years pointed out interesting developments. Deloitte (2023) has shown that the objectives of GBS shifted. Besides the core objective to save costs and standardize efficiency of processes, other objectives such as the development of capabilities, the risk reduction and the access to abroad talent pools increased. Another study result, depicted in *Figure 1,* was conducted by HFS Research in 2023 asking over 600 executives across Global 2000 enterprises has shown that on third of the executives expect the focus of business services in 2-3 years to be on “new sources of leveraging data driven insights and emerging technology”. In parallel, the “cost saving” focus will decrease by half of its overall share compared to the current state (Gupta and Fersht, 2023).

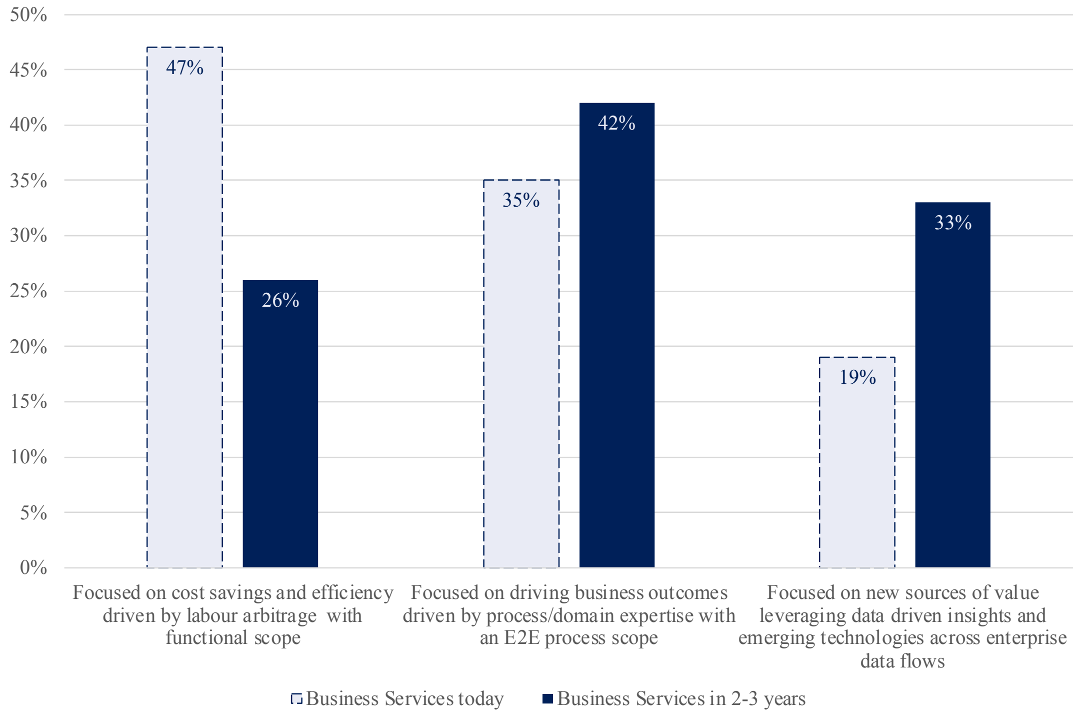


Figure 1 GBS objective survey

As the current dynamics in GBS transformation regarding objectives and technology adoption where depicted, the following chapter examines the influence of technological advancements on the strategic vision of GBS, with a particular emphasis on automation potential.

2.2 Process Automation Technology

This chapter describes the comparative technologies of Robotic Process Automation (RPA) and the differences to intelligent and learning models like Machine Learning (ML) or GenAI. Afterwards this thesis aims to present in more detail in the findings section which use cases can best be addressed with the help of AI.

Extensive analysis of the given technologies regarding their development and functional classification can be found in literature. The predominant technologies currently in use are RPA, ML, and AI. *Figure 2*, which was developed based on Becker (2019), Siyong (2018), Anthony Jnr. (2022), Arntz et al. (2019), Kasych & Vochozka (2019), Lai (2017) and Park & Choi (2019), shows the development process of automation technologies in terms of their functionality.

In the current era of intense competition, BPO has emerged as a strategic measure for organisations to improve their competitiveness by leveraging technology to create value for customers (Ndiiri & Kilika, 2021). From a strategic perspective, technology enables organisations to focus on their core business processes by outsourcing non-core business functions and creating value for end users (Karamyshev, 2019).

By combining RPA and ML, synergies can be achieved that leverage the benefits of both technologies (Moraes et al., 2022). The developmental stages that were cited will be further elaborated in the following to illustrate their functional differentiation.

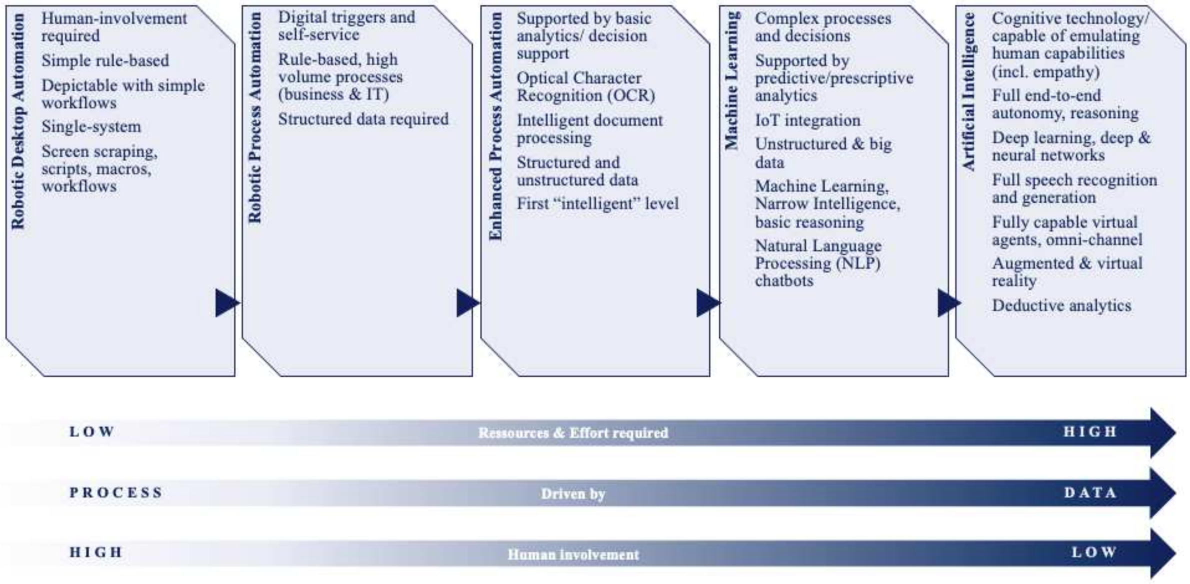


Figure 2 The evolution of Process Automation

RPA and Robotic Desktop Automation (RDA) are two automation technologies that differ significantly in their human involvement, use cases and tool security (Dilmegani, 2023).

RDA is primarily designed to assist humans in their tasks. This is done, for example, through help within individual applications, such as toolbars, macros, or wizards, which can support many front- and back-office activities (Jesse, 2023). Due to limitation reasons, RDA will not be part of the recommendations of this thesis.

RPA, on the other hand, involves the use of a variety of technologies that have been trained based on tasks performed by humans to automate repetitive actions (Osman, 2019). This is done through the independent application and execution of scripts containing sequences (Bosco et al., 2019) to connect interactions between e.g. desktop and web applications (Leno et al., 2021). Today, RPA is one of the most important technologies in process automation (Brandstatter et al., 2023). According to empirical studies, the use of RPA bots has already successfully realised optimisation potential in various sectors (Osman, 2019; Sobczak & Ziora, 2021). In use, RPA tools can i.e. open files, select fields and values in spreadsheets or formulas, or copy and paste records content (Osman, 2019). They were able to automate simple activities up to 100% (Feio & Dos Santos, 2022).

Willcocks (2017) describes there are three different types of robotic automation, which require different prerequisites for implementation. Firstly, RDA requires no programming skills. It processes an instruction and then "forgets why it exists". Secondly, Enterprise or server RPA is primarily used to automate IT processes related to governance, security, architecture, or infrastructure and requires no programming. Finally, Professional RPA requires programming and is primarily used in Accounting and Supply Chain Management.

RPA has several advantages and disadvantages. Advantages include increased efficiency, speed and reliability (Chugh et al., 2022), integration with AI (Jha et al., 2021a) and resource savings (Li et al., 2023). The susceptibility to human error in repetitive manual data entry, which is circumvented by RPA, thus leads to a fundamental increase in productivity and the quality of the end results (Chugh et al., 2022). On the other hand, it should be noted that RPA scripts tend to be limited to minor complex processes and therefore be used for simpler application examples (Moraes et al., 2022). As RPA programming is not as intelligent as AI, tasks such as evaluating human behaviour or complex input-based decisions cannot be performed by RPA (Gotthardt et al., 2020).

The following chapter explains the functionality and individual models of AI and shows how they differ in the application compared to RPA.

2.3 Artificial Intelligence

Alan Turing laid the theoretical foundation for AI by raising the research question “Can machines think?” (Turing, 1950). The Turing test he developed involves testing the intelligence of a machine and states that a computer can be considered intelligent if it is indistinguishable from a human in correspondence (Haenlein & Kaplan, 2019).

Five years later, the term "Artificial Intelligence" was mentioned in literature for the first time (Anyoha, 2017). In 1955, mathematician John McCarthy wrote in a book section on AI that any aspect of learning or any function of intelligence can be described exactly in such a way that machine simulations of it can be made (McCarthy et al., 1955).

Although the programmes fulfilled the criterion of intelligence, they had to be abandoned in the 1970s and 1980s due to limited computing power (Anyoha, 2017). For this reason, intelligent systems were further developed in the direction of knowledge, expertise and role-based intelligence (Haenlein & Kaplan, 2019).

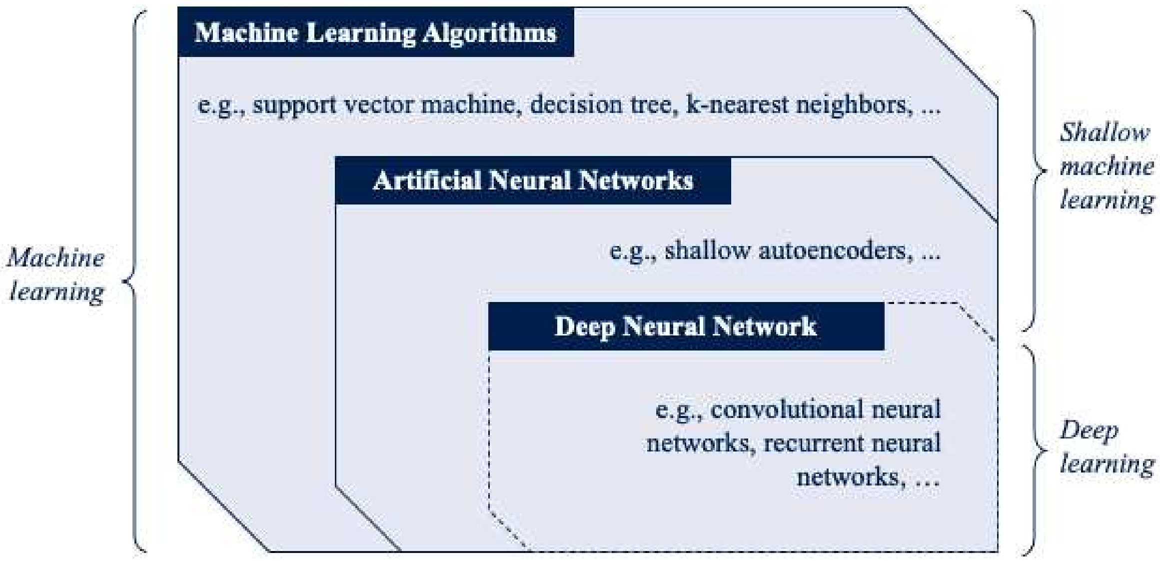


Figure 3 Different stages of intelligent machines

According to the European Commission Joint Research Centre (2020), examples of this are Dendral or MYCIN, which were able to implement solutions to problems in specific subject areas. Due to the limitations of ambiguous and uncertain information, the next step was taken in the 1990s towards models based on statistics and probability mathematics. As these models used comparable arithmetic operations, they laid the foundation for the AI we know today. These models gave rise to data-based models and networks such as ML and neural networks (NN). The momentous breakthrough of AI with natural language processing (NLP), computer vision and robotics has increasingly spread into many areas such as speech recognition. Since the turn of the millennium, further breakthroughs such as Big Data (BD), extensions of Deep Learning (DL) and NNs have driven development forward.

The framework depicted in *Figure 3* was based on Janiesch et al. (2021), Wirtz (2022), Goodfellow et al. (2016) and shows that AI Networks and Deep Neural Network (DNN) are a part of ML Algorithms. Their capabilities are different and so are the use cases in practice. Janiesch et al. (2021), Wirtz (2022) and Goodfellow et al. (2016) suggest that the realm of intelligent machines do involve the following three layers to contribute to their evolving capabilities:

At the foundational layer, ML algorithms form a diverse category equipped to learn from data, enabling informed decision-making without explicit programming. Examples include decision trees, support vector machines, and linear regression, making them versatile for tasks like classification and regression analysis.

Above ML algorithms, Artificial Neural Networks (ANNs) emulate the brain's architecture. Comprising interconnected nodes, or neurons, ANNs process information and learn patterns through iterative training (Janiesch et al., 2021). This layer excels in tasks such as pattern recognition, image processing, and natural language understanding.

Within ANNs, DNNs stand out as a specialized subset. Featuring multiple layers, DNNs model complex relationships and hierarchical features, making them adept at intricate tasks like image and speech recognition, as well as NLP (LeCun et al., 2015).

In the interplay of these layers, overlaps occur. ML algorithms may leverage NN structures, while DNNs represent a specific subset within ANNs (Janiesch et al., 2021). The central intersection signifies scenarios where all layers—ML algorithms, ANNs, and DNNs—are concurrently applicable (Goodfellow et al., 2016). Understanding these layers elucidates the hierarchical relationships inherent in the academic discourse of ML. Now that the overarching categories have been introduced, the following section takes a closer look at the different types of AI.

Joshi (2019) described AI from functionality and capability perspective. *Figure 4* shows that the different categories of AI are divided into two categories (capabilities and functionalities). The capability types include Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI) and Artificial Super Intelligence (ASI), while the functionality types include Reactive Machines, Limited Memory, Theory of Mind and Self-Awareness.

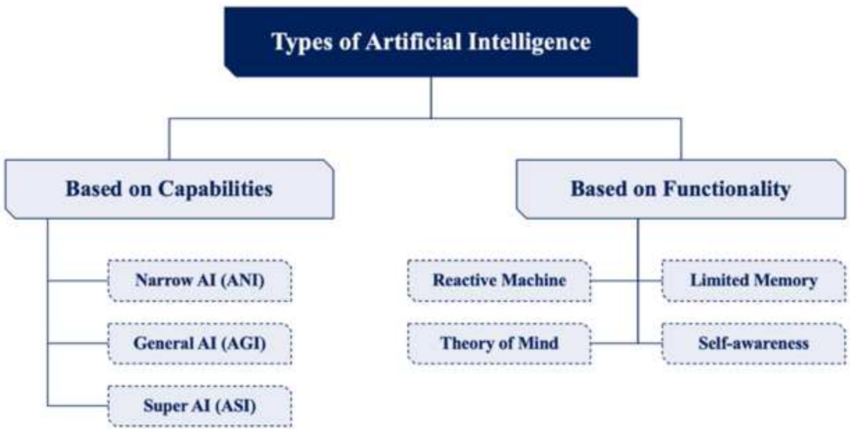


Figure 4 Types of Artificial Intelligence

ANI or weak AI refers to AI systems that have been trained specifically for one domain of application. These systems can only apply their underlying commands to the domain for which they were trained (Searle, 1980). Examples include Siri or Alexa (speech recognition) and facial recognition software (image recognition) (Marr B. , 2021b). AGI or strong AI, is described in literature as having humans-like capabilities (Goertzel, 2014; Torre, 2017).

Unlike ANI, AGI masters cognitive abilities such as learning, problem solving or adapting to new situations (Liem et al., 2018). Buttazzo (2023) mentions that at present, however, AGI is still a theoretical model on which research is being conducted into how it might be implemented in the future. ASI describes AI systems that exceed human capabilities. This stage is currently purely hypothetical. In further course of this thesis, AGI and ASI will not be considered due to the lack of technological progress.

According to Hintze (2016) in terms of its functionality. The first type are reactive machines, which are the simplest form of AI systems. They have no memory, only process current events and respond with action sequences based on the specific training domains (Marr B. , 2021a). An example is IBM's Deep Blue chess computer, which calculates the optimal play based on the current state of the chessboard (Joshi, 2019). The second type is limited memory systems, which has the ability to learn from past events and act based on current situation. They are called limited memory systems because they can only store a limited amount of historical data and incorporate it into the decision-making process. A practical example would be self-driving cars that make decisions about driving patterns based on traffic events (Hintze, 2016). The third type in this category is Theory of Mind, which refers to systems that can understand and interpret thoughts, emotions, and social and human-like behaviour. As with AGI and ASI, there are currently no practical examples other than the hypothetical ones. This type of AI is still in the realm of theoretical research and has not been realised in practical applications (Joshi, 2019). The last type is self-awareness, where AI systems realise their own self-image, thoughts and emotions. This type is also not found in practice, as research and development is not as advanced (Buttazzo, 2023). Theory of mind and self-awareness, as well as AGI and ASI, are not included in the studies due to the practical applications that will be considered in the following.

In summary, the journey of AI is an ongoing one, with the future promising even more developments in this rapidly evolving field (Russell et al., 2022). There are different types of AI, each with different capabilities and potential applications. While ANI and limited memory AI are prevalent in current applications, the theoretical concepts of AGI, ASI, reactive machines, and theory of mind represent the potential future evolution of AI.

2.3.1 Machine Learning

ML is broadly defined as a computational method that uses experience and data inputs to improve accurate predictions (Mohri et al., 2018). As shown in *Figure 2*, advanced intelligence in technology begins at the level of ML (Wirtz, 2022). It gives computers the ability to learn without being explicitly trained (Brown, 2021). ML involves the development of algorithms and statistical models that allow computer systems to improve their performance on a particular task through experience (Nogueira et al., 2019). ML models, such as NNs and decision trees, are trained on labelled datasets to make predictions or decisions without being explicitly programmed (Mohri et al., 2018). For example, pre-trained models such as ELMo, OpenAI GPT and BERT have achieved impressive results in various NLP tasks, such as question answering and natural language inference (Zaib et al., 2020).

The capabilities of ML are well described in the literature. In contrast to RPA, ML can analyse large datasets (Mohri et al., 2018) and recognise patterns, enabling organisations to make data-driven decisions (Wuest et al., 2016). This ability allows ML to detect errors and derive appropriate decisions (Mulongo, 2022). In addition, much more complex tasks can be fully automated with ML (Hanif et al., 2021).

However, there are also limitations to the application of ML. The underlying algorithms are highly dependent on data quality and volume (Lopes et al., 2022). Li (2009) reports incomprehensible "black boxes" that make it very difficult to understand the decisions made (Ribeiro et al., 2016; Rudin, 2019). There are also ethical concerns, mainly related to biases in terms of objectivity and discrimination (Z. Chen, 2023).

In summary, ML is a powerful technology, but one that should not be used without concern. In the next section, the specifics of DL will be explained in more detail.

2.3.2 Deep Learning

DL is a methodological extension of ML (Goodfellow et al., 2016) and has gained momentum and application since the DL revolution in 2012 (Dean, 2020). The ability of DL to establish non-intuitive relationships in complex data sets and to learn from areas other than those trained has expanded the field of ML research (Janiesch et al., 2021).

The functionality of AI based on ANNs (Janiesch et al., 2021) was extended to DNNs in DL and is differentiated by the ability to learn from the training data and new data inputs (LeCun et al., 2015). As with ANNs, the structures of DNNs are modelled on those of the human brain (Goodfellow et al., 2016) and consist of a large number of layers and nodes (M. Chen et al., 2019). The depth of the network is achieved through the layering of numerous processing layers that analyse the processed data (Goodfellow et al., 2016, LeCun et al., 2015). In this way, DL has already shown to outperform human capabilities under certain conditions (Madani et al., 2018; Silver et al., 2016).

However, to utilise the advantages of DNNs in the corporate environment, a number of hurdles need to be overcome. Feuerriegel et al. (2023) states that, in addition to appropriate implementation methodologies and model accuracy, interpretability play a decisive role.

2.3.3 Generative Artificial Intelligence

GenAI refers to a category of AI that has the ability to generate creative output (e.g. images, text, or audio). This output in the form of is based on pattern recognition of the data on which the GenAI has been trained (Janiesch et al., 2021). Like ML and DL, the GenAI model to be trained relies on complex data sets that form the basis of the output (Feuerriegel et al., 2023; Goodfellow et al., 2016; Janiesch et al., 2021). Modelling techniques such as Generative Adversarial Networks (GANs) (Goodfellow et al., 2020), Variational Autoencoders (VAEs) (Mescheder et al., 2017), and diffusion and transformer-based models (Rose, 2023) are used to provide realistic output.

GANs use an adversarial training model where the generator network generates the content and the discriminator network verifies the authenticity of the generated content (Creswell et al., 2018). VAEs are expressive latent variable models that can be used to train complex probability calculations from data sets (Mescheder et al., 2017). Diffusion models or denoising diffusion probabilistic models, mainly known from image generation, are less used in practice due to their time-consuming backward sampling process (Rose, 2023). Transformer-based models or Large Language Models (LLMs) such as ChatGPT (Safar, 2021) can analyse relationships between parts of the input to further improve the quality of the output (Rose, 2023).

All models improve through feedback (Ziegler et al., 2020). The difference in the learning process is that the models learn either visually or data-based, requiring very large datasets (Feuerriegel et al., 2023). By querying the quality of the output, the algorithm can improve itself (Safar, 2021).

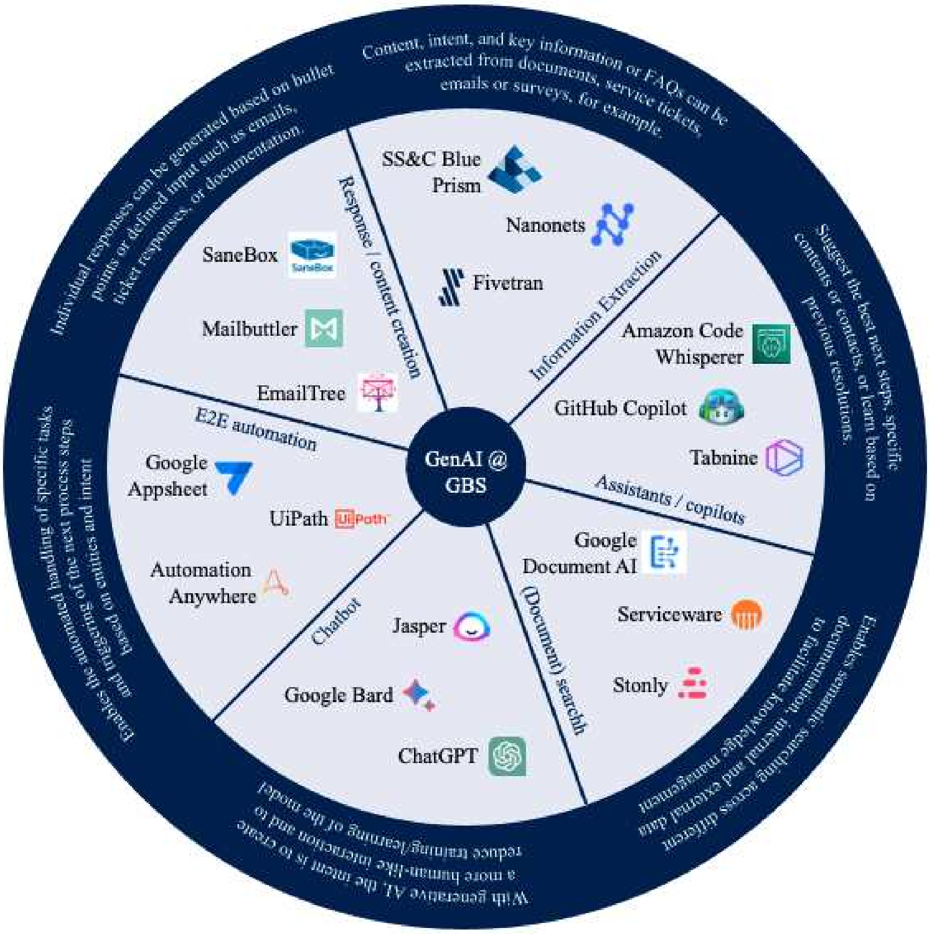


Figure 5 GenAI for GBS: Use Cases

Figure 4 was based on Rose (2023), Bohnsack et al. (2023), Raidops (2023) and Siemens (2022) shows how broad the application of AI is. The AI wheel, which has been shows exemplary areas of GenAI application within a GBS unit. In the following the use cases along the GenAI wheel will be explained:

End-to-End (E2E) automation involves using GenAI to automate entire business processes from start to finish. Technically this is not feasibly only with GenAI but with a combination of intelligent technology This includes tasks that may span across different departments or functions within the GBS unit (Jones, 2020). In that manner GenAI can assist to automate the E2E process of e.g. source-to-pay (GEP, 2023).

According to Rose (2023), Chatbots leverage NLP or ML to interact with users through textual or voice-based conversations. In a GBS context, chatbots can handle routine queries, provide information, and assist with various tasks. Deploying a chatbot to handle employee queries related to policies, benefits, or general inquiries about GBS services.

Reid (2023) states that searching operations with the help of GenAI can enhance document search capabilities by understanding contextual queries and retrieving relevant information from a variety of documents and data sources. Implementing a smart search tool powered by GenAI to quickly locate specific information within a vast repository of documents, contracts, and reports.

Information Extraction involves using GenAI to automatically identify and extract relevant data or insights from unstructured sources, such as documents, emails, and reports. Utilizing GenAI to extract key data points from vendor contracts, including terms, conditions, and important dates, to facilitate contract management (Rose, 2023).

Assistants/Co-pilots work alongside human employees, providing support, guidance, and suggestions throughout various tasks. They can learn from user interactions and adapt to user preferences. Implementing an AI co-pilot to assist employees in the preparation of financial reports, offering real-time suggestions for data analysis and report formatting (Böckeler, 2023).

Rose (2023) states that, response- & content creation can generate human-like responses and create content based on input data, user queries, or predefined parameters by utilizing GenAI. This can be applied to various communication channels. Using GenAI to draft responses to customer inquiries, create standard operating procedures (SOP), or generate initial drafts of reports, saving time for human employees.

After the use technical and functional capabilities as well as the use case potentials of intelligent solutions where explained the following section will provide an overview of the regulatory landscape for AI implementation projects within the European Union (EU) zone.

2.4 Regulatory Compliance, Governance and Security

In the GBS environment within the EU, the implementation of AI can be influenced and slowed by various issues. These include, for example, data security, the traceability of algorithms and the legal framework of the GBS region (McKinsey, 2023). As explained in more detail in the findings, Nebula's main business is located in Europe and must therefore comply with e.g. the General Data Protection Regulation (GDPR) framework of the EU for the implementation of technology (Goddard, 2017; Labadie & Legner, 2023; Martins et al., 2020; Tikkinen-Piri et al., 2018). Besides that, this chapter describes the status of the regulatory framework in the EU regarding data security and risk assessment.

Since the technology underlying AI involves complex data processing and requires extensive knowledge bases (training data), such technologies are usually connected to many different third-party applications, the IT backbone and a wide variety of data sensitivities, which makes them vulnerable to various harmful types of attacks (Junklewitz et al., 2023; Labadie & Legner, 2023). According to the GDPR in the EU, the data owner, who determines the purposes and means of data processing, remains responsible for the security of the data. However, the controller may use the services of third parties who act as processors. These processors must enter contractual obligations set out in the GDPR, including the implementation of appropriate security measures. It is recommended to set up a data protection contract that ensures the relationship and obligations between the controller and the processor.

Providing guideline for AI implementation, the European Commission (EC) published the AI Act in April 2021, in which the regulatory framework within the EU was proposed, stating that “the promotion of AI-driven innovation is closely linked to the Data Governance Act, the Open Data Directive and other initiatives under the EU strategy for data, which will establish trusted mechanisms and services for the re-use, sharing and pooling of data that are essential for the development of data-driven AI models of high quality” (European Commission, 2021, p. 6). In December 2023, the European Parliament published answers regarding the AI Act to expand and clarify the basis created for companies.

According to the European Commission (2021) and Junklewitz et al. (2023), the recently adopted AI Act sets out four principles for the cybersecurity of AI-driven software in companies:

The first principle mentions that the contents of the enacted should refer to "high-risk AI systems" and not to lower-risk models in general. The second principle focuses on the risk assessment of the AI Act. When implementing AI, the interfaces of its models to non-AI components of the system must be assessed in terms of vulnerability and limitations. Two methods were presented for risk assessment, firstly the risk assessment according to Article 9 “Risk management systems” and secondly according to Recital 51 of the AI Act and Annex II (2.8). The former tests the general risk and the latter the cybersecurity risk. This means that even if a tool is generally categorized as high-risk, it may still have a low cybersecurity risk. Depending on the cybersecurity risk assessment, the AI Act also proposes an implementation methodology. The third principle states that AI software should not be treated differently from other complex software architectures. This means that known cybersecurity approaches of cloud and Internet of Things (IoT) systems should be applied here (Hansen & Venables, 2023). The risk score should depend on the application design and intended area of use. It is also recommended that high-risk classified AI components should also be implemented and secured in an AI-specific manner, e.g. by specifically training the model against damaging attacks. The last concept notes that the security of AI is limited at the present time and limits the standards published in the AI Act. This means that all newer models after 2021 cannot necessarily be secured with the recommended standards from the AI Act.

Europe is focussing on the creation of enforceable regulations and provisions for AI and robotics. It emphasises the need for government regulation alongside self-regulation by companies (De Laat, 2021; Langman et al., 2021). The regulatory framework is part of a broader digital transformation strategy (Kitsios & Kamariotou, 2021) and includes topics such as data sharing, data protection, transparency of algorithms, data standardisation and cross-platform interoperability (He et al., 2019; Sun & Medaglia, 2019) with the aim of aligning AI with corporate strategy and sustainability goals (Kitsios & Kamariotou, 2021). Analysing the elements of risk that AI can bring to companies and implementing appropriate risk assessment processes are crucial for the safe and effective introduction of GenAI (Barta & Görcsi, 2021).

Russell et al. (2022) emphasise that ML systems require a different adoption, verification and validation compared to GenAI, as well as a different approach that has not yet been developed. Therefore, Kroll & Berzins (2022) have developed a list of recommendations to help with the implementation of AI. This list is considered in more detail in chapter *6. Recommendations*.

In addition, the "technology-organisation-environment" framework and "innovation diffusion theory" are used to examine the adoption of AI at an organisational level, highlighting the impact of technology, organisation and environment, including regulatory support and competitive pressures (Y. Chen et al., 2022; Kar et al., 2021).

In summary, although there are certain limitations to securing AI models, those systems are still considered compliant if risks are effectively mitigated at the AI component level.

3 Methods

This thesis focuses on exploring and analysing the implementation of AI in Nebula GBS. To gain understanding of the possibilities and challenges associated with this implementation, a qualitative and exploratory research approach was chosen.

The research approach was selected for its suitability in delving into complex structure and underlying processes to capture diverse perspectives on the current state of Nebula GBS. The qualitative method is particularly apt for the exploration of the underlying topic.

The central research questions forming the foundation of the investigation were clearly formulated at an early stage of research planning. These questions center on how the use of AI can maximize growth potential and productivity (Q1), the areas within Nebula's GBS where AI has the most significant impact (Q2), the influence of AI implementation on work processes (Q3), and what sets AI implementation in GBS apart from regular business practices (Q4).

The interviewee sample included ten individuals of different relevant positions within Nebula GBS, ranging from team leadership through mid-management to C-level. This way, the sample enables a comprehensive perspective on the maturity status as well as challenges and potentials of AI implementation into Nebula's GBS. Participant selection was closely aligned with Nebula's thesis advisor to ensure representativeness for digital transformation within the organization.

Data collection took place through qualitative expert interviews lasting between 30 to 120 minutes. The choice of video calls facilitated personal interaction despite spatial distances. The interviews were recorded upon consent, transcribed, and conducted using a pre-developed and individually adjusted questionnaire. Further details to be found in *Appendix II*.

Relevant variables for the study were clearly defined. The applied measurement instruments, consisting of questions in the interview guide, were checked for validity and reliability.

Figure 6 shows that the research was conducted systematically, with the process documented from interview guideline drafting to evaluation and discussion of the code-based findings.

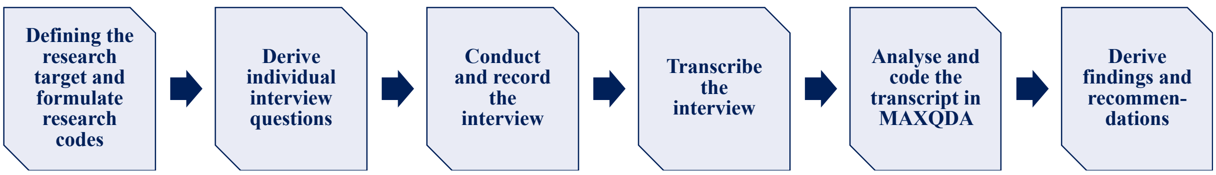


Figure 6 Interview methodology

The data analysis was conducted through deductive coding, utilizing the AWS AI Maturity Matrix (2022), IBM AI Analysis (2021), MMC Venture (n.d.) and HFS Research (2023), stating five main categories: "People" (51 codes), "Technology" (64 codes), "Data" (11 codes), “Strategy” (33 codes), and “Governance” (39 codes). The length of the codes varied from word groups to more extended paragraphs. The total duration of the audio recordings amounted to 581 minutes, with a total transcription length of 208 pages. Ethics data processing was ensured during the research process. Anonymity and confidentiality of data were ensured, and sensitive information were anonymized for publication purposes of this thesis. An overview of the coding process can be found in *Appendix IV*.

The study openly reflects potential limitations affecting the transferability of results. Potential influencing factors are carefully considered. To ensure reliability, Cohen’s Kappa was employed, involving a partial recoding of the dataset by a second coder. On a sample of 10%, a reliability overlap of 82% resulted between both coders was observed. This result underscores the accuracy of the analysis and confirms the reliability of the applied Mayring method (Mayring, 2000; 2010). Reliability was maintained through clear documentation of the research process and the application of standardized procedures, including transcription and coding. This ensures that the research findings are reproducible and would reliably lead to similar results if the study were repeated.

Validity was ensured using established measurement instruments, clear definition of variables, and the selection of a diverse sample. This guarantees that the study indeed measures what it is intended to measure, and the results are applicable to the entire population of Nebula GBS.

Overall, this methodology provides a comprehensive and structured approach to investigating AI implementation at Nebula’s GBS. The following chapters provide a detailed statement of the interview’s findings and the development of a derived implementation blueprint for AI in GBS.

4 Findings

4.1 AI Implementation Roadmap

The GBS AI Readiness Assessment covers some of the most important areas that management can consider before the implementation of AI can begin. It distinguishes between different stages and can be found as an Excel template in *Appendix V*.

It should be mentioned at the outset that various quality criteria have been applied that are included in the AI readiness assessment. The implementation of AI is not considered mandatory, but should have a positive impact on effectiveness, productivity, and the working atmosphere. It should lead to existing and future employees being introduced to the topic of AI and to the establishment of forward-looking rules and standards for dealing with and taking responsibility for intelligent technology. These goals should be pursued for strategic reasons to prevent a shift in corporate culture.

The aim of the assessment is to determine whether the structures of Nebula GBS are sufficient to start developing and implementing AI initiatives. Pioneer companies in AI research have already published papers proposing such processes for regular companies (IBM, 2021; elementAI, 2022).

Figure 7 is derived from the (Siemens, 2023) results and represents an exemplary development process for the implementation of AI in GBS units. Furthermore, the figure is leaning on *Table 1* for the GBS context and is additionally based on the AI Maturity Frameworks of IBM (2021), elementAI (2022), MMC Ventures (2019) and the reports of Deloitte (2021; 2022; 2023), PwC (2021; 2023), BCG (2023) and McKinsey (2023).

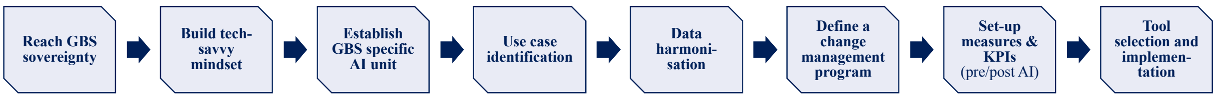


Figure 7 Roadmap: AI for GBS

Firstly, the political structure of the GBS must be examined. This ranges from a separate legal entity to a pure service centre. As described in the chapter *Literature Review*, both cases means differ in their requirements for the process, with independence being a particularly important criterion. If the parent company in the corporate structure dictates which technologies are to be used, for example, this hampers the process considerably. The more the GBS can determine its own structure, the easier it will be to integrate new technologies and structures. If this is not the case, it is advisable to establish a company-wide and centralised data and AI strategy. This is outside the scope of this thesis.

The development of a GBS-specific strategy applies not only to the technological aspect, but also to the employment strategy and the associated alignment of the employees. The development of a technology-savvy mindset within GBS is essential to successfully meet the challenges and opportunities of advancing digitalisation. This focus aims to prepare employees for AI and ensure that they develop the necessary mindsets and skills for dealing with intelligent technologies.

In order to justify to the examination of use cases and infrastructural possibilities, Kroll & Berzins (2022), recommends the formation of a central task force of qualified employees. In terms of project management, this unit is tasked with the objective of carrying out a concrete analysis of the possibilities in the technology used and the data required for this. In future, the members will represent the Subject Matter Experts within the GBS. *Figure 8* shows the corresponding governance model in the *6. Recommendations* chapter.

If the sovereignty and autonomy of the GBS is guaranteed, it is recommended that the security, availability and quality of the GBS-specific data be addressed first. The aim of this investigation is the application-based harmonisation of the data. If lager data harmonisation and consolidation initiative i.e. data lake or data warehouse already exists for the GBS specifically, this is already a good prerequisite. Data lakes and data warehouses are technologies in which all available data in structured or unstructured form is brought together (Nambiar & Mundra, 2022). Those initiatives bring a certain level of data quality to the GBS and could potentially allow the adoption for AI to process it. Utilising data mining, LLMs are not able to access the GBS data set and only prompting outputs according to the sensitivity level of data yet (Lareo, 2023). The combination of a data lake in combination with a LLMs could enable the automatic labelling, metadata creation, improved data search and discovery, easing the data analysis process (Barjatiya, 2023).

The geographical location of the GBS is particularly important for data security. Nebula’s GBSs are in the eurozone and are therefore subject to the provisions of the European GDPR. It is emphasised that other regions such as the USA or China are not comparable in this respect, as different standards apply here (Zenonos, 2023). Therefore, if data security is decided centrally within the main company, in case of doubt, the GBS may be subject to significantly higher standards than are required based on the region. This would also diminish the full potential of progress.

The situation with the GBS technology stack is like that of data. To shape the digital strategy of GBS as precisely as possible, it should also be examined here whether the fast-moving technologies in GBS can be prioritised, provided that reliable business cases are available.

In addition, depending on the personnel structure of the GBS, an appropriately dedicated change management programme should be set up with corresponding responsible persons. This includes i.e. the organisation of training courses for the newly introduced technology, the development of an internal communication strategy or the creation of an environment that is ready for change (Saha, 2023).

Now that all the foundations for implementation have been laid, a framework for measurability must be created. To this end, specific KPIs should be defined that enable performance to be compared. These can include topics such as process efficiency, cost savings or susceptibility to errors. It is important here that the KPIs can be applied both to the status before implementation and to the status after implementation (Murphy, 2023).

Having presented the roadmap to AI readiness of a GBS entity in this chapter, the next chapter looks at analysing use cases that could be carried out by the AI task force, for example.

4.2 Use Case Analysis: RPA vs. AI

In business process optimisation, the strategic selection between RPA and AI is paramount. As the chapters *2.2 Process Automation Technology* and *2.3 Artificial Intelligence* provided the functional capabilities of automation technology, this chapter describes the decision-making process on the direct comparison of RPA and AI usage. *Figure 8* depicts the decision-making process between those two technologies based on Jha et al. (2021) in a simplified form.

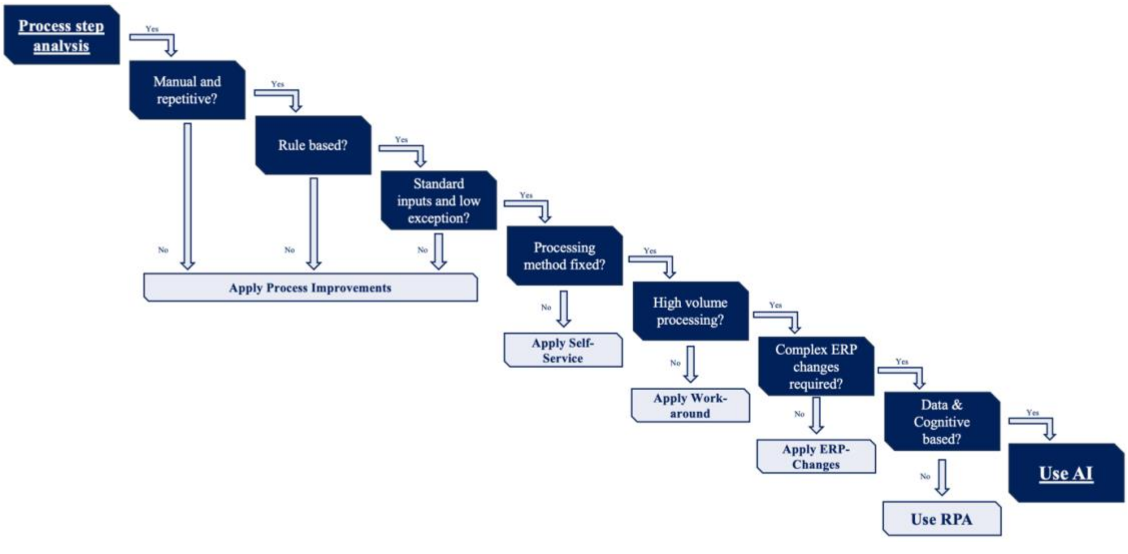


Figure 8 Decision-making process: AI vs. RPA

When faced with manual and repetitive processes, RPA emerges as a pragmatic solution. Tasks characterized by routine and rule-based operations, such as data entry, invoice processing, or data migration, are ideal candidates for RPA implementation. RPA excels in automating these tasks, freeing up HR for more complex and value-added activities.

Rule-based operations find a natural fit with RPA. Processes governed by clearly defined rules and structured data are well-suited for automation through RPA bots. The deterministic nature of RPA allows for the seamless execution of tasks, adhering strictly to pre-established rules and guidelines.

In scenarios where inputs are standardized, and exceptions are infrequent, RPA proves its efficiency. RPA bots thrive in environments where data inputs exhibit consistency, enabling them to perform tasks with high accuracy and minimal deviation.

Processes with a fixed and unchanging processing method align seamlessly with the capabilities of RPA. RPA is designed to follow predefined workflows, making it an ideal choice for tasks where the processing steps remain constant over time.

For tasks involving high volumes of repetitive data processing, RPA offers a scalable solution. The ability of RPA bots to handle large volumes of transactions with speed and accuracy makes them indispensable for organizations dealing with significant data throughput.

When contemplating complex Enterprise Resource Planning (ERP) changes, AI applications come into play. In a scenario where an organization is transitioning from one ERP system to another, RPA bots can be employed to automate the extraction of relevant data from the existing ERP system. The bots can then transform and input this data into the new ERP system, streamlining the migration process and ensuring accuracy in data transfer. This use case leverages RPA's capabilities to handle routine, rule-based tasks involved in data migration between ERP systems. (Eddy, 2019)

In processes demanding cognitive abilities and data interpretation, AI emerges as the preferred option. AI applications, powered by ML algorithms, excel in tasks that involve data analysis, pattern recognition, and decision-making based on contextual understanding.

The decision to deploy RPA or AI hinges on the specific characteristics of the business process at hand. RPA excels in automating rule-based, repetitive tasks with high volumes and standardized inputs. In contrast, AI is the preferred choice for processes requiring adaptability, cognitive abilities, and handling dynamic scenarios. A thoughtful analysis of the nature of the task, considering factors such as rule complexity, data variability, and the need for cognitive interpretation, will guide organizations toward selecting the most suitable automation solution for optimal efficiency and effectiveness.

4.3 Interview Results

After the methodology of the empirical data collection of this thesis was explained in the previous chapter, the following section presents the initial situation of Nebula's GBS and evaluates the results.

Nebula is operating a GBS with a focus on process optimisation, cost reduction and continuous improvement through innovative technologies. One of the strategic goals of Nebula GBS is to increase productivity while minimising costs. In addition, there is an interest in enlarging Nebula's talent pool. There is an interest in becoming an accelerator for the development of human capital to attract and train talent from the industry. Recognising the importance of AI in recruiting talent, especially IT professionals such as developers and data analysts, Nebula sees AI as a strategic enabler to attract sought-after professionals in the highly competitive IT labour market.

The following chapters relate to two E2E processes for which GBS is responsible as a COP. The focus here is particularly on the T&E and H2R processes. These processes were selected in connection with the integration of intelligent software solutions. The data collection process was based on Willcocks et al. (2017), which emphasises the need to promote corporate culture.

4.3.1 Strategy and People

As already described in the previous chapters, the structures of a GBS in the corporate world are not comparable to those of a large corporation. This also applies to the implementation of AI at Nebula. Currently, processes are transferred to the Nebula GBS using the lift-and-shift approach. This initially provides for the transfer of multinational company processes to the GBS and subsequent optimisation by the GBS. This process enables a structured harmonisation and standardisation of the transferred processes.

When looking at the workforce, it becomes clear that very young people work here, with an average age of approximately 33, according to the interviewees. The working culture is described as integrative, tech-savvy, and open-minded. There is a high level of motivation for the digital transformation, the realisation of optimisation potential and the further development of process automation. The professional background is diverse and enables problem solving through creativity, different perspectives and the breaking down of conventional methods and processes. What all interviewees have in common is their attitude towards continuous improvement. All ten interviewees used the term "continuous improvement", which represents the principle of Nebula's GBS structure. The experts stated that mandatory training must be completed at the beginning of their work in the GBS, which is intended to motivate new employees to think and act innovatively. This provides employees with the necessary knowledge and tools. In addition, there are regular training sessions on topics such as continuous improvement methods, the application of lean methods, design thinking and the application of theoretical knowledge to identify improvement cases.

The organisation of the teams continues to promote the basic attitude and the omnipresent goal of continuous improvement of tasks and processes. Responsibility for the teams lies with the team leaders, or nominated champion for continuous improvement within the team, who report to senior management (see C-Level). New initiatives for process optimisation are also communicated, which require the approval of GBS management for implementation. This means that the identification and formulation of optimisations is decentralised in the teams and ends with a central implementation process. There is also the option of submitting company-wide use cases via the central Nebula GenAI platform. These are then evaluated and categorised according to application area, required technology and department.

There are two different models regarding process responsibility and the affiliation of the people working on the process. On the one hand, the "Alpha" model is used, in which the activities are transferred from another company unit to GBS, where they are subsequently assigned responsibility. In the case of Nebula, this has already been implemented for several processes (e.g. H2R and T&E). The second delivery model is named "Beta" (ß), in which the activity is carried out locally in the GBS, but responsibility lies with a team outside the GBS. This model requires the approval and support of the team to be supported and the company's central management to implement initiatives. It can be shown that in the Alpha model there is more freedom to offer the agile structures of a GBS the opportunity to optimise processes, as there is less need for coordination with other stakeholders.

4.3.2 Technology

Consequently, the maturity level of technologies and data is analysed, and the application of low- and no-code AI is discussed. As Nebula already uses automation technologies (e.g. RPA) for process optimisation, particular attention is paid to the area of intelligent software solutions for business processes. The implementation of the RPA one-shot automation in Nebulas GBS supports the e-filing for documents. This automation not only transitioned colleagues to more engaging tasks but also streamlined routine processes, minimizing risks in archiving and e-filing. The applications help to make processes more efficient and agile. Besides this, the maturity level of intelligent automation technology used shows room for improvement, particularly in optical character recognition (OCR). An implementation could support the extraction of structured and unstructured data from physical and digital documents across all processes. More specific use cases are described in chapter *6. Recommendations*.

It became clear in the interviews that the maturity level of technology, data (databases) and processes does not appear to be sufficiently harmonised for AI to be used across systems. Added to this are the challenges of implementing OCR. The corresponding need became clear in the expert discussions on the H2R and T&E process.

Other tools such as chatbots are planned to be used for customer service to increase the response rate and answer as many questions as possible automatically. It should be noted that chatbots, which can only rely on simpler automated responses such as ML algorithms, can therefore only answer simple enquiries. Human contact persons are still required for all more complex answers.

Nebula GBS uses a cloud-based workspace, including several applications to create dashboards and automate processes. It should be noted here that, according to the interviewees, this is not yet widespread enough to realise its full potential.

First steps of process mining utilised to realise optimising potentials within processes. The corresponding software in use could offer new capabilities for processing documents and unstructured data. For example, the process orchestration capabilities act as a large workflow layer to manage E2E processes and trigger automation for multiple solutions.

To increase efficiency, GenAI is currently used for debugging written programme code in compliance with the internal company's data protection regulations. It could be investigated whether this is a larger use case to support with the appropriate tool support.

4.3.3 Data

The introduction of new technologies in GBS requires dealing with bureaucratic structures and external regulators. Risk management is a key determinant in the implementation of new technologies. Various factors such as data storage and compliance (e.g. GDPR) must be accounted. The technology stack plays an important role in the framework conditions for robust and secure backend systems.

As part of the interview series, experts were asked specifically about the topic of data. This revealed a tendency for data availability, transparency, and standardisation within the GBS to be stated as "in developed". This poses a challenge for processing and reporting, particularly due to the partially inconsistent data structure.

The processing of sensitive information, especially personal data (e.g. in HR), requires the approval of legal authorities and adherence to compliance guidelines to ensure data protection. The harmonisation and standardisation of data is a continuous improvement initiative, with dedicated teams monitoring the handling of master data in different regions and departments. The feasibility to find a balance between data usability and individual protection needs should be evaluated. In line with the GDPR, data could be cleansed and aggregated to lower sensitivity levels to protect personally identifiable information. As a resulting use case from the interviews, it was suggested that a data lake or warehouse could be created, with a LLM accessing the GBS data. This could provide instantaneous answers to queries.

The lack of a direct connection to department-specific databases sometimes leads to manual downloads and time-consuming corrections to data records. For example, the Human Resource Information System (HRIS) in use does not offer the option of customisation via programming codes, e.g. via Python scripts. Scripts are a subcategory of programming language aim to e.g. "glue" application to each other (Ousterhout, 1998). As this is not possible, preparing and analysing the data can take several days, depending on the technology stack used. However, by using suitable tools and a database environment, this process could be reduced to one day. As such cases significantly hinder further automation, one goal could be to improve the utilisation and storage of data. In this context, initiatives are being developed to make the handling and management of data more user-friendly.

4.3.4 Corporate Governance and Organisation

The governance and organisation within Nebula are currently organised centrally across the GBS. One of the examples that could be illustrated here through the interview series is data governance, which is managed centrally and across organisations by 17 data officers. It is noteworthy that all functions have their own data officer, but there is no dedicated one for Nebula's GBS.

Nebula's GBS team structure is designed for efficient transitions and process optimization. Key roles, including a transition manager, business analyst, and process champions, operate under leadership. Resources include two exclusive RPA developers, showcasing a commitment to technology. When defining and suggesting new optimization use cases, financial backing from the management team is imperative for cost-associated initiatives. Regular monthly and bi-weekly meetings focus on e.g. recruitment status or transition progress. Nebula prioritizes technological change with a dedicated change management team, emphasizing continual improvement. This organisational structure underlines the solid set-up for digital transformation initiatives.

Finally, another result of the interviews can be mentioned. It can be deduced that the more the relevant experts have dealt with the processing of data in their normal working environment, the more sceptical they were about the implementation of AI at the current stage. This means that the professional opinion within the GBS consisted of a mixture of motivated definition of use cases and scepticism towards their implementation.

4.4 Answering the Research Questions

Q1: How can the use of AI maximise growth potential and productivity at Nebula's GBS?

To increase productivity and further optimise processes in Nebula GBS, there is no way around using intelligent data-based tools. Currently RPA, ML will most likely have the largest impact due to the given data harmonisation status. However, initiatives can also be combined to create greater synergy potential of "hyper automation" (Jones, 2020) which goes beyond this thesis' scope. The focus should be on the use case to select the optimal technological basis. The blueprint developed in chapter *4.1 AI Implementation Roadmap* and *Appendix 1* and *Appendix 5* can be utilized for this purpose. If the goal is to automate repetitive tasks in the sense of productivity, this could already be solved with either RPA or ML algorithms and the use of corresponding technology endpoints. Productivity could also be increased using GenAI, which can be achieved, for example, with the automatic completion of writing (e.g. emails), code (e.g. when creating scripts) or external communication through chatbots.

However, other factors are decisive for the strategic growth of the workforce. If the aim is to utilise intelligent solutions in the future, care should be taken to ensure that new employees have the appropriate basic technical understanding. One option could be to use appropriate vocabulary in the job advertisements and to assume previous experience with the use of intelligent process automation at a basic level. (BCG, 2023)

Q2: Were has AI the largest impact in Nebula's GBS operations?

According to the interviews, the potentially greatest impact of AI can be found in three different business areas. Firstly, in the process steps that involve standardised documents. Specifically, this includes the extension of applications with OCR modules in the existing technology stack. This includes the automation of e-invoicing or smart contracting. Secondly, in communication with third parties in the form of automatically answered emails or chatbots. Thirdly, increasing productivity with the help of AI assistants that can, for example, support the writing of text or code to avoid manual errors. A tool selection for the named use cases cannot be carried out within the scope of this thesis for capacity reasons.

Q3: Which impact will the implementation of AI into a GBS unit have on the way of working?

The interviews made it clear that employees are highly motivated to adopt intelligent software solutions. Collaboration with such solutions is generally welcomed. Despite outdated fears of technology potentially replacing jobs, there is little doubt that the integration of new technologies would have a lasting impact on work culture. The introduction of emerging technologies in GBS is strongly favoured by the age structure and mindset of the workforce. The agility present in GBS, which tends to be lacking in large and complex organisations, can be effectively mapped. However, it has been established that parts of the workforce are interested in retaining certain manual intermediate steps. These serve as regeneration time during working hours. In this context, a more detailed study of the influence of AI on general productivity would be advisable.

Q4: What differentiates an AI implementation into a GBS unit from regular business?

In addition to the differentiating features of a GBS mentioned in the previous research questions, further points can be mentioned that distinguish a GBS implementation from a regular implementation.

In this case, the GBS is politically subordinate to its corporate group. It adheres to the guidelines and policies of the parent company and must also comply with the security standards specified in the EU. Although processes for which the GBS is responsible tend to be faster than in complex corporate structures, the data quality and harmonisation here is different to that of the parent company.

In summary, it can be said that AI implementation is currently more difficult than in the parent company due to the availability and harmonisation of data, but this can be overcome with targeted projects due to the effectiveness of the processes and the favourable workforce setup.

5 Discussion

The results of this thesis suggest the further development of AI and intelligent solutions in the context of GBS in direction of process automation and productivity enhancement. This is countered partially by concerns from the literature, which describe the replaceability of people in the tasks to be automated (Brauner et al., 2023). The following chapter will discuss which other factors need to be weighed up before implementation in GBS can be undertaken.

The implementation of AI raises several ethical issues that must be carefully considered before implementation. The interpretation of the results and the comparison with the literature provide important insights for the ethical discussion. An ethical dilemma arises with large projects that lead to the long-term dismissal of employees who cannot be retained in retraining programmes. The profitability of such projects through the dismissal of especially younger employees considered "redundant" conflicts with the research objectives here (Howells, 2023). This raises the question of how the dilemma between increasing productivity (Q1) and the potential need for mass redundancies (Q3) should be assessed. Mental health also plays an important role in post-implementation monitoring, as various studies in recent years have found links between AI awareness and implementation and burnout, fear of job loss, demotivation, uncertainty, and psychological stress (Kong et al., 2021; Presbitero & Teng-Calleja, 2022).

Responsibility and transparency in algorithmic decisions are of central importance (Russell et al., 2022). Hill (2020) refers to the term "explainable AI" (XAI) which describe that decisions made algorithmically must be understood within the organisation up to the executive level and there must be a clear line of accountability. The organisation must take responsibility for decisions made by algorithms.

Effective AI governance goes beyond mere compliance with the law and emphasises the development of fair, transparent and accountable AI systems (Anthony Jnr., 2022). This is critical to ensure that AI applications meet ethical standards and minimise potential biases (Hill, 2020). The challenge is to strike a balance between the potential of automation to reduce the workforce, which could impact organisational culture, and the simultaneous pursuit of increased productivity and long-term cost reduction. Nebula GBS could take a pragmatic approach, starting with small-scale AI implementation, which is also recommended by Willcocks et al. (2017). However, this is in ethical conflict with the question of whether restructuring Nebula human resources is justifiable in accordance with the values of responsibility. The ethics behind the decision to make people redundant must be carefully considered to ensure that the implementation of AI does not come at the expense of social responsibility (Brauner et al., 2023).

The limitation and research outlook follow. The interview series was limited exclusively to Nebula employees, which provided a limited perspective on the topic under investigation. To further develop the thesis of human capital development, it would be advisable to analyse additional GBS. This could enable a broader view. In the further development of the topic, particular attention should be paid to the current regulations that provide the framework for such projects, for example from the EC and the European Parliament. When applying the blueprint developed, it should be noted that the topic under discussion is extremely dynamic and benefits from the continuous monitoring of the latest trends. Especially regarding the next step of Autonomous Business Services, an in-depth feasibility study of the implementation should be carried out. This evaluation will help to adequately assess the feasibility and identify potential challenges.

6 Recommendations

6.1 General Recommendations

When selecting tools in the future, the selection criteria should be more focussed on the integration capability of AI. Until then, it is recommended that RPA continues to be used as extensively as possible for the automation of repetitive activities, as this involves less effort and, depending on the area of application, lower risks.

The strategy for implementing AI should include an overarching approach in GBS as also suggested by BCG (2023). Before implementing an AI strategy, it is emphasised that a solid data strategy is crucial. Depicted in *Figure 9,* Kroll & Berzins (2022) recommends the establishment of a "Data Use Review Board" for this purpose, which can help to ensure compliance with the guidelines developed for handling data. This board could take over the activities of standardizing AI processes across countries and formulate SOPs to describe AI-related activities and how to execute them. It could be imaginable to create a platform where all GBS employees can submit new use cases which could be evaluated through the board. This way the AI culture It is important that these standards are in line with EU regulations.

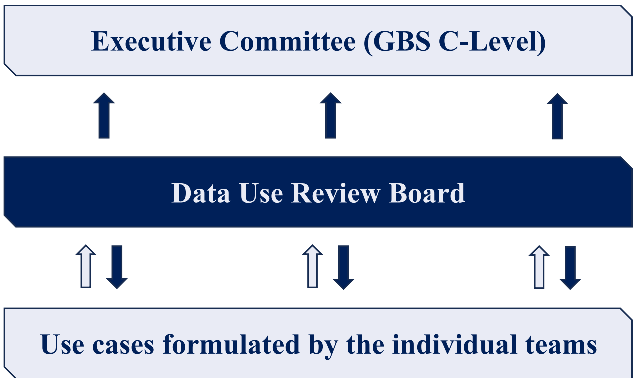


Figure 9 Corporate AI Governance

Thoroughly analysing the risk elements of AI, establishing appropriate risk assessment processes, and assembling teams of specialists to identify cross-GBS use cases are fundamental and should be developed and expanded in a GBS-specific manner for a safe and effective introduction of AI (BCG, 2023). The economic aspects of the use cases should also be carefully analysed.

When implementing AI, strategic consideration should be given to whether the responsibility of activities and processes can be increased by the GBS (e.g. in the COP model) in terms of decision-making freedom and the realisation of optimisation potential.

Beyond the two focussed processes, AI can provide significant support in the source-to-pay process (e.g. in supplier evaluation). The source-to-pay approach is presented as a viable option for comprehensive process management, aiming for an E2E perspective covering master data, controlling, sourcing, purchase requisition, purchase order processing, goods receipts, invoice processing, payments, and performance closing. As the selection of tools is beyond the scope of this paper, it is recommended to evaluate if existing providers offer potential expansion options in these fields.

It is also recommended to introduce the integration of an educational path as a "Citizen Developer" within the HRIS tool used. This could enable non-informatic educated individuals to explore the features and capabilities of intelligent no- and low-code applications. In addition, it is conceivable to lay the foundations for understanding Web 3.0 in parallel. The aim of this pathway is for graduates to learn how to deal with data in a playful way and no longer see it as an obstacle, but as an opportunity for further education. For intrinsically motivated or particularly good graduates, a subsequent programme for learning programming languages would be conceivable. In this way, the GBS could be transformed into a strategic and technically trained catalyst for innovation.

Due to the nature of the organisation, it is advisable for Nebula GBS to develop its own digital strategy and recruitment strategy that is independent of the parent company. The speedboat model can be used for this. This methodology describes the framework conditions for a rapid innovation process with the help of the empowerment of one or more small units that receive special support for the further development of products or services by the parent company (Rothwell, 1994). A GBS specific use case analysis and strategy development is necessary to adequately consider the different core activities and corresponding data of the GBS. This way POC based on cleared data could be created with existing employees.

In conclusion, the implementation of AI requires centralised planning, including data protection, risk assessment and strategic decisions (Barta & Görcsi, 2021). If GBS processes are to be mapped holistically by AI-based applications, it is worth looking at the relevant market. If the mindset depicted here is maintained, this can be the key to successful transformation. The structure of Nebula GBS offers a very good starting point for becoming a future talent accelerator in the Nebula organisation.

6.2 Use Case: H2R

The H2R involved several steps between a candidate joining and leaving. Therefore, intelligent algorithms during the complete employee lifecycle, including recruitment, onboarding, training, development, payroll, benefits, retention, and offboarding (Nosratabadi et al., 2022;

Nawaz, 2019; Z. Chen, 2023; Ghory & Ghafory, 2021). BCG (2023) describes that GenAI in HR has a very strong influence on automation and increasing productivity.

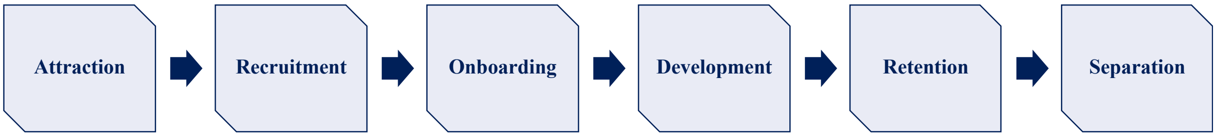


Figure 10 Employee lifecycle

Throughout the employee lifecycle as described by Cattermole (2019), shown in *Figure 10,* AI can play an important role in performance management and feedback. The deployment of AI in providing performance feedback to employees, particularly veteran employees, can yield positive outcomes, suggesting the potential for tiered AI deployment strategies within organisations (Tong et al., 2021). AI technology can be harnessed for talent acquisition, as it has the potential to transform how GBS recruit and select employees (Johnson et al., 2021). In this context, AI can be utilised to optimise recruitment processes, analyse candidate data, and enhance the selection of suitable candidates. By employing AI for talent acquisition, GBS can enhance productivity, efficiency, quality, and competitive power in acquiring and managing talent (Hmoud & Várallyai, 2022). Furthermore, AI can aid in the development of fairness rules for talent intelligence management systems, ensuring unbiased recruitment and talent management practices (Köchling & Wehner, 2020). The use of AI in recruitment can also contribute to the development of new job opportunities and improve job quality, creating employment opportunities in high-end technical talent positions (Bian et al., 2022). Once employees are onboarded, AI can facilitate learning and development initiatives. Employees' learning behaviour in the context of AI collaboration can be influenced by the job demand-control model, highlighting the potential for AI to optimize learning experiences and skill development.

GenAI is now also increasingly appearing in the advertising of market leaders. Workday, Oracle and SAP are advertising the new technology in the field of human capital management. Use cases here include first-touch interviews, writing job descriptions or application sourcing with corresponding position recommendations (Li et al., 2023). LLMs trained by the software providers are used for this purpose. It is recommended that existing Nebula partners are approached and asked about the corresponding possibilities.

In conclusion, Nebula's GBS H2R process can benefit from the strategic integration of AI. From talent acquisition to employee development and eventual departure, AI can optimise processes, enhance decision-making, and contribute to the overall success of the GBS organisation.

6.3 Use Case: T&E

The T&E process includes the management and reimbursement of various costs incurred in business activities, such as travel expenses, entertainment costs and other overheads (C. X. Chen et al., 2012). The adoption of innovative technologies has been emphasised as an important dimension for examining the technological context of T&E processes (Zhu et al., 2006). These expenditures are often associated with corporate governance issues as they may be subject to asymmetric behaviour (Balafoutas et al., 2015). It should be noted that the travel and expense process can be susceptible to fraudulent activity, as some individuals may attempt to reimburse illegitimate expenses with falsified or inflated receipts (Li & Zhou, 2021).

Examples of applications include invoice data extraction, invoice duplicate identification or reconciliation (Uhura, 2023). Purchased software or modules contain sufficient visual recognition and language models trained by the software provider, which offer highly reliable data extraction from invoice documents (Alistair, 2023). As interview results state that one of the existing partners is already using AI in their modules, it is recommended to ask whether such services can be adopted within the GBS. The advantage here is a lower risk in the development of such technologies. If an extension is requested via existing certified software, the regulations that apply in the EU must already be followed by the manufacturers.

References

Literature

Alistair, K. (Director). (2023, December 15). *Leveraging Generative AI for Revolutionising Travel & Expense Management: The SAP Concur Approach* [Mp4]. https://www.youtube.com/watch?v=c-scjZW7mEY&t=15s

Anthony Jnr., B. (2022). Toward a collaborative governance model for distributed ledger technology adoption in organizations. *Environment Systems and Decisions*, *42*(2), 276–294. https://doi.org/10.1007/s10669-022-09852-4

Arntz, M., Gregory, T., & Zierahn, U. (2019). *Digitalization and the future of work: Macroeconomic consequences*. *ZEW-Leibniz Centre for European Economic Research*. http://hdl.handle.net/10419/200063

Balafoutas, L., Beck, A., Kerschbamer, R., & Sutter, M. (2015). The hidden costs of tax evasion. *Journal of Public Economics*, *129*, 14–25. https://doi.org/10.1016/j.jpubeco.2015.06.003

Barta, G., & Görcsi, G. (2021). Risk management considerations for artificial intelligence business applications. *International Journal of Economics and Business Research*, *21*(1), 87. https://doi.org/10.1504/IJEBR.2021.112012

BCG, Roghé, F., Kleebaur, S., Gupta, R., Sissimatos, E., & Toma, A. (2023). *For Global Business Services, Generative AI Creates Four Big Opportunities* (p. 44). BCG. https://www.bcg.com/publications/2023/genai-creates-four-key-business-opportunities

Bian, Y., Lu, Y., & Li, J. (2022). Research on an Artificial Intelligence-Based Professional Ability Evaluation System from the Perspective of Industry-Education Integration. *Scientific Programming*, *2022*, 1–20. https://doi.org/10.1155/2022/4478115

Bosco, A., Augusto, A., Dumas, M., La Rosa, M., & Fortino, G. (2019). Discovering Automatable Routines from User Interaction Logs. In T. Hildebrandt, B. F. Van Dongen, M. Röglinger, & J. Mendling (Eds.), *Business Process Management Forum* (Vol. 360, pp. 144–162). Springer International Publishing. https://doi.org/10.1007/978-3-030-26643-1_9

Brandstatter, C., Tschandl, M., & Mitterback, C. (2023). A Generic Process Model for the Introduction of Robotic Process Automation in Financial Accounting. *Proceedings of the 2023 9th International Conference on Computer Technology Applications*, 12–18. https://doi.org/10.1145/3605423.3605464

Brauner, P., Hick, A., Philipsen, R., & Ziefle, M. (2023). What does the public think about artificial intelligence?—A criticality map to understand bias in the public perception of AI. *Frontiers in Computer Science*, *5*, 1113903. https://doi.org/10.3389/fcomp.2023.1113903

Buttazzo, G. (2023). Rise of artificial general intelligence: Risks and opportunities. *Frontiers in Artificial Intelligence*, *6*, 1226990. https://doi.org/10.3389/frai.2023.1226990

Cattermole, G. (2019). Developing the employee lifecycle to keep top talent. *Strategic HR Review*, *18*(6), 258–262. https://doi.org/10.1108/SHR-05-2019-0042

Chen, C. X., Lu, H., & Sougiannis, T. (2012). The Agency Problem, Corporate Governance, and the Asymmetrical Behavior of Selling, General, and Administrative Costs*. *Contemporary Accounting Research*, *29*(1), 252–282. https://doi.org/10.1111/j.1911-3846.2011.01094.x

Chen, M., Challita, U., Saad, W., Yin, C., & Debbah, M. (2019). Artificial Neural Networks-Based Machine Learning for Wireless Networks: A Tutorial. *IEEE Communications Surveys & Tutorials*, *21*(4), 3039–3071. https://doi.org/10.1109/COMST.2019.2926625

Chen, Y., Hu, Y., Zhou, S., & Yang, S. (2022). Investigating the determinants of performance of artificial intelligence adoption in hospitality industry during COVID-19. *International Journal of Contemporary Hospitality Management*, *35*(8), 2868–2889. https://doi.org/10.1108/IJCHM-04-2022-0433

Chen, Z. (2023). Ethics and discrimination in artificial intelligence-enabled recruitment practices. *Humanities and Social Sciences Communications*, *10*(1), 567. https://doi.org/10.1057/s41599-023-02079-x

Cherbakov, L., Galambos, G., Harishankar, R., Kalyana, S., & Rackham, G. (2005). Impact of service orientation at the business level. *IBM Systems Journal*, *44*(4), 653–668. https://doi.org/10.1147/sj.444.0653

Chugh, R., Macht, S., & Hossain, R. (2022). Robotic Process Automation: A review of organizational grey literature. *International Journal of Information Systems and Project Management*, *10*(1), 5–26. https://doi.org/10.12821/ijispm100101

Creswell, A., White, T., Dumoulin, V., Arulkumaran, K., Sengupta, B., & Bharath, A. A. (2018). Generative Adversarial Networks: An Overview. *IEEE Signal Processing Magazine*, *35*(1), 53–65. https://doi.org/10.1109/MSP.2017.2765202

De Laat, P. B. (2021). Companies Committed to Responsible AI: From Principles towards Implementation and Regulation? *Philosophy & Technology*, *34*(4), 1135–1193. https://doi.org/10.1007/s13347-021-00474-3

Dean, J. (2020). 1.1 The Deep Learning Revolution and Its Implications for Computer Architecture and Chip Design. *2020 IEEE International Solid- State Circuits Conference - (ISSCC)*, 8–14. https://doi.org/10.1109/ISSCC19947.2020.9063049

Deloitte. (2021). *2021 Global Shared Services and Outsourcing Survey Report* (Global Shared Services and Outsourcing, p. 27) [Survey]. Deloitte Development LLC. https://www2.deloitte.com/content/dam/Deloitte/ie/Documents/Consulting/global-shared-services-2021-150621.pdf?logActivity=true

Deloitte. (2022). *Deloitte Global Outsourcing Survey 2022 "Beyond outsourcing: Entering a new sourcing ecosystem" Navigating talent, technology, and new ways to outsource* (Global Outsourcing Survey, p. 16) [Survey]. Deloitte LLP. https://www2.deloitte.com/us/en/pages/operations/articles/global-outsourcing-survey.html

Deloitte. (2023). *Global Shared Services and Outsourcing Survey* (p. 29) [Survey]. Deloitte Development LLC. https://www2.deloitte.com/us/en/pages/operations/articles/shared-services-survey.html
elementAI. (2022). *The AI Maturity Framework* (p. 39).
Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial Intelligence and Business Value: A Literature Review. *Information Systems Frontiers*, *24*(5), 1709–1734. https://doi.org/10.1007/s10796-021-10186-w
European Commission. (2021). *REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL LAYING DOWN HARMONISED RULES ON ARTIFICIAL INTELLIGENCE (ARTIFICIAL INTELLIGENCE ACT) AND AMENDING CERTAIN UNION LEGISLATIVE ACTS*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A52021PC0206
European Commission. (2023). *Artificial Intelligence – Questions and Answers*.
European Commission Joint Research Centre. (2020). *AI Watch, historical evolution of artificial intelligence: Analysis of the three main paradigm shifts in AI.* Publications Office. https://data.europa.eu/doi/10.2760/801580
European Parliament. (2023, December 9). *Artificial Intelligence Act: Deal on comprehensive rules for trustworthy AI* [Press Room]. https://www.europarl.europa.eu/news/en/press-room/20231206IPR15699/artificial-intelligence-act-deal-on-comprehensive-rules-for-trustworthy-ai
Feio, I. C. L., & Dos Santos, V. D. (2022). A Strategic Model and Framework for Intelligent Process Automation. *2022 17th Iberian Conference on Information Systems and Technologies (CISTI)*, 1–6. https://doi.org/10.23919/CISTI54924.2022.9820099
Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2023). Generative AI. *Business & Information Systems Engineering*. https://doi.org/10.1007/s12599-023-00834-7
Ghory, S., & Ghafory, H. (2021). The impact of modern technology in the teaching and learning process. *International Journal of Innovative Research and Scientific Studies*, *4*(3), 168–173. https://doi.org/10.53894/ijirss.v4i3.73
Goddard, M. (2017). The EU General Data Protection Regulation (GDPR): European Regulation that has a Global Impact. *International Journal of Market Research*, *59*(6), 703–705. https://doi.org/10.2501/IJMR-2017-050
Goertzel, B. (2014). Artificial General Intelligence: Concept, State of the Art, and Future Prospects. *Journal of Artificial General Intelligence*, *5*(1), 1–48. https://doi.org/10.2478/jagi-2014-0001
Gomathy, C. K., & Rajalakshmi, S. (2014). A software quality metric performance of professional management in service oriented architecture. *Second International Conference on Current Trends In Engineering and Technology - ICCTET 2014*, 41–47. https://doi.org/10.1109/ICCTET.2014.6966260
Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT press.
Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2020). Generative adversarial networks. *Communications of the ACM*, *63*(11), 139–144. https://doi.org/10.1145/3422622
Gotthardt, M., Koivulaakso, D., Paksoy, O., Saramo, C., Martikainen, M., & Lehner, O. (2020). Current State and Challenges in the Implementation of Smart Robotic Process Automation in Accounting and Auditing. *ACRN Journal of Finance and Risk Perspectives*, *9*(1), 90–102. https://doi.org/10.35944/jofrp.2020.9.1.007
Grefen, P., Mehandjiev, N., Kouvas, G., Weichhart, G., & Eshuis, R. (2009). Dynamic business network process management in instant virtual enterprises. *Computers in Industry*, *60*(2), 86–103. https://doi.org/10.1016/j.compind.2008.06.006
Grover, P., Kar, A. K., & Dwivedi, Y. K. (2022). Understanding artificial intelligence adoption in operations management: Insights from the review of academic literature and social media discussions. *Annals of Operations Research*, *308*(1–2), 177–213. https://doi.org/10.1007/s10479-020-03683-9
Guida, M., Caniato, F., Moretto, A., & Ronchi, S. (2023). The role of artificial intelligence in the procurement process: State of the art and research agenda. *Journal of Purchasing and Supply Management*, *29*(2), 100823. https://doi.org/10.1016/j.pursup.2023.100823
Haenlein, M., & Kaplan, A. (2019). A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. *California Management Review*, *61*(4), 5–14. https://doi.org/10.1177/0008125619864925
Hanif, H., Md Nasir, M. H. N., Ab Razak, M. F., Firdaus, A., & Anuar, N. B. (2021). The rise of software vulnerability: Taxonomy of software vulnerabilities detection and machine learning approaches. *Journal of Network and Computer Applications*, *179*, 103009. https://doi.org/10.1016/j.jnca.2021.103009
Hansen, R., & Venables, P. (2023, June 8). Introducing Google's Secure AI Framework [The Keyword]. *SAFETY & SECURITY*. https://blog.google/technology/safety-security/introducing-googles-secure-ai-framework/
He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. *Nature Medicine*, *25*(1), 30–36. https://doi.org/10.1038/s41591-018-0307-0
Hill, C. W. L. (2022). *Global business today* (12e, international student edition ed.). McGraw Hill.
Hmoud, B., & Várallyai, L. (2022). Artificial Intelligence In Talent Acquisition, Do we Trust It? *Journal of Agricultural Informatics*, *12*(1). https://doi.org/10.17700/jai.2021.12.1.594
IBM. (2021). *AI Maturity Framework for enterprise application* (p. 13).
Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets*, *31*(3), 685–695. https://doi.org/10.1007/s12525-021-00475-2
Jha, Dr. R., Upadhyay, G. M., & Institute of Innovation In Technology & Management, GGSIP University Delhi, India. (2021b). Novel Approach for Robotic Process Automation with Increasing Productivity and Improving Product Quality using Machine Learning. *International Journal of Engineering and Advanced Technology*, *10*(3), 103–109. https://doi.org/10.35940/ijeat.C2192.0210321
Jha, N., Prashar, D., & Nagpal, A. (2021a). Combining Artificial Intelligence with Robotic Process Automation—An Intelligent Automation Approach. In K. R. Ahmed & A. E. Hassanien (Eds.), *Deep Learning and Big Data for Intelligent Transportation* (Vol. 945, pp. 245–264). Springer International Publishing. https://doi.org/10.1007/978-3-030-65661-4_12

Johnson, R. D., Stone, D. L., & Lukaszewski, K. M. (2021). The benefits of eHRM and AI for talent acquisition. *Journal of Tourism Futures*, *7*(1), 40–52. https://doi.org/10.1108/JTF-02-2020-0013

Junklewitz, H., Harmon, R., André, A., Evas, T., Soler Garrido, J., & Sanchez Martin, J. (2023). *Cybersecurity of artificial intelligence in the AI Act: Guiding principles to address the cybersecurity requirement for high risk AI systems.* Publications Office. https://data.europa.eu/doi/10.2760/271009

Kakabadse, N., & Kakabadse, A. (2000). Critical review – Outsourcing: A paradigm shift. *Journal of Management Development*, 59.

Kar, S., Kar, A. K., & Gupta, M. P. (2021). Modeling Drivers and Barriers of Artificial Intelligence Adoption: Insights from a Strategic Management Perspective. *Intelligent Systems in Accounting, Finance and Management*, *28*(4), 217–238. https://doi.org/10.1002/isaf.1503

Karamyshev, A. N. (2019). Decision-Making Model at Large Machine-Building Enterprises. *HELIX*, *9*(5), 5395–5399. https://doi.org/10.29042/2019-5395-5399

Kasych, A., & Vochozka, M. (2019). Modernization processes in the modern world: Methodology, evolution, tendencies. *Espacios*, *7*.

Kitsios, F., & Kamariotou, M. (2021). Artificial Intelligence and Business Strategy towards Digital Transformation: A Research Agenda. *Sustainability*, *13*(4), 2025. https://doi.org/10.3390/su13042025

Köchling, A., & Wehner, M. C. (2020). Discriminated by an algorithm: A systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment and HR development. *Business Research*, *13*(3), 795–848. https://doi.org/10.1007/s40685-020-00134-w

Kong, H., Yuan, Y., Baruch, Y., Bu, N., Jiang, X., & Wang, K. (2021). Influences of artificial intelligence (AI) awareness on career competency and job burnout. *International Journal of Contemporary Hospitality Management*, *33*(2), 717–734. https://doi.org/10.1108/IJCHM-07-2020-0789

Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal*, *44*(6), 1425–1452. https://doi.org/10.1002/smj.3387

Kroll, J. A., & Berzins, V. (2022). *Understanding, Assessing, and Mitigating Safety Risks in Artificial Intelligence Systems*.

Labadie, C., & Legner, C. (2023). Building data management capabilities to address data protection regulations: Learnings from EU-GDPR. *Journal of Information Technology*, *38*(1), 16–44. https://doi.org/10.1177/02683962221141456

Lacity, M., Yan, A., & Khan, S. (2017). *Review of 23 Years of Empirical Research on Information Technology Outsourcing Decisions and Outcomes*. Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2017.632

Lai, P. (2017). The literature review of technology adoption models and theories for the novelty technology. *Journal of Information Systems and Technology Management*, *14*(1), 21–38. https://doi.org/10.4301/S1807-17752017000100002

Langman, S., Capicotto, N., Maddahi, Y., & Zareinia, K. (2021). Roboethics principles and policies in Europe and North America. *SN Applied Sciences*, *3*(12), 857. https://doi.org/10.1007/s42452-021-04853-5

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Leno, V., Polyvyanyy, A., Dumas, M., La Rosa, M., & Maggi, F. M. (2021). Robotic Process Mining: Vision and Challenges. *Business & Information Systems Engineering*, *63*(3), 301–314. https://doi.org/10.1007/s12599-020-00641-4

Li, P., Bastone, A., Mohamad, T. A., & Schiavone, F. (2023). How does artificial intelligence impact human resources performance. Evidence from a healthcare institution in the United Arab Emirates. *Journal of Innovation & Knowledge*, *8*(2), 100340. https://doi.org/10.1016/j.jik.2023.100340

Li, X., & Zhou, X. (2021). Autonomy, incentive and trade: How does trade liberalisation reshape corporate decentralisation in China? *The World Economy*, *44*(10), 3051–3069. https://doi.org/10.1111/twec.13105

Liem, C. C. S., Langer, M., Demetriou, A., Hiemstra, A. M. F., Sukma Wicaksana, A., Born, M. Ph., & König, C. J. (2018). Psychology Meets Machine Learning: Interdisciplinary Perspectives on Algorithmic Job Candidate Screening. In H. J. Escalante, S. Escalera, I. Guyon, X. Baró, Y. Güçlütürk, U. Güçlü, & M. Van Gerven (Eds.), *Explainable and Interpretable Models in Computer Vision and Machine Learning* (pp. 197–253). Springer International Publishing. https://doi.org/10.1007/978-3-319-98131-4_9

Lin, K., Zhao, Y., Kuo, J.-H., Deng, H., Cui, F., Zhang, Z., Zhang, M., Zhao, C., Gao, X., Zhou, T., & Wang, T. (2022). Toward smarter management and recovery of municipal solid waste: A critical review on deep learning approaches. *Journal of Cleaner Production*, *346*, 130943. https://doi.org/10.1016/j.jclepro.2022.130943

Lopes, D. D., Cunha, B. R. D., Martins, A. F., Gonçalves, S., Lenzi, E. K., Hanley, Q. S., Perc, M., & Ribeiro, H. V. (2022). Machine learning partners in criminal networks. *Scientific Reports*, *12*(1), 15746. https://doi.org/10.1038/s41598-022-20025-w

Madani, A., Arnaout, R., Mofrad, M., & Arnaout, R. (2018). Fast and accurate view classification of echocardiograms using deep learning. *Npj Digital Medicine*, *1*(1), 6. https://doi.org/10.1038/s41746-017-0013-1

Marr, B. (2019). *Artificial intelligence in practice: How 50 successful companies used artificial intelligence to solve problems* (First edition). Wiley.

Martins, F., Amaral, L., & Ribeiro, P. (2020). Implementation of GDPR: Learning with a Local Administration Case Study. In H. Santos, G. V. Pereira, M. Budde, S. F. Lopes, & P. Nikolic (Eds.), *Science and Technologies for Smart Cities* (Vol. 323, pp. 205–216). Springer International Publishing. https://doi.org/10.1007/978-3-030-51005-3_19

Maslak, O. I., Maslak, M. V., Grishko, N. Ye., Hlazunova, O. O., Pererva, P. G., & Yakovenko, Y. Yu. (2021). Artificial Intelligence as a Key Driver of Business Operations Transformation in the Conditions of the Digital Economy. *2021 IEEE International Conference on Modern Electrical and Energy Systems (MEES)*, 1–5. https://doi.org/10.1109/MEES52427.2021.9598744

Matytsin, D. E., Dzedik, V. A., Markeeva, G. A., & Boldyreva, S. B. (2023). “Smart” outsourcing in support of the humanization of entrepreneurship in the artificial intelligence economy. *Humanities and Social Sciences Communications*, *10*(1), 13. https://doi.org/10.1057/s41599-022-01493-x

McCarthy, J., Minsky, M. L., Rochester, N., Corporation, I. B. M., & Shannon, C. E. (1955). *A PROPOSAL FOR THE DARTMOUTH SUMMER RESEARCH PROJECT ON ARTIFICIAL INTELLIGENCE*.

McKinsey. (2023). *The state of AI in 2023: Generative AI's breakout year* (p. 24) [Survey]. Black Quantum. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year#/

Mescheder, L., Nowozin, S., & Geiger, A. (2017). *Adversarial Variational Bayes: Unifying Variational Autoencoders and Generative Adversarial Networks*.

MMC Ventures. (2019). *SoAI2019_Playbook_WEB.pdf*.

Mohri, M., Rostamizadeh, A., & Talwalkar, A. (2018). *Foundations of machine learning* (Second edition). The MIT Press.

Moraes, C. H. V. D., Scolimoski, J., Lambert-Torres, G., Santini, M., Dias, A. L. A., Guerra, F. A., Pedretti, A., & Ramos, M. P. (2022). Robotic Process Automation and Machine Learning: A Systematic Review. *Brazilian Archives of Biology and Technology*, *65*, e22220096. https://doi.org/10.1590/1678-4324-2022220096

Mulongo, Y. (2022). An integrated Machine Learning Model for Manufacturing industry. *Indonesian Journal of Computer Science*, *11*(1). https://doi.org/10.33022/ijcs.v11i1.3021

Nambiar, A., & Mundra, D. (2022). An Overview of Data Warehouse and Data Lake in Modern Enterprise Data Management. *Big Data and Cognitive Computing*, *6*(4), 132. https://doi.org/10.3390/bdcc6040132

Nawaz, N. (2019). Artificial Intelligence Interchange Human Intervention in the Recruitment Process in Indian Software Industry. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3521912

Ndiiri, A., & Kilika, J. (2021). Business Process Outsourcing and Firm Performance of Selected Real Estate Firms in Nairobi City County, Kenya. *International Journal of Business Management, Entrepreneurship and Innovation*, *3*(3), 139–150. https://doi.org/10.35942/jbmed.v3i3.221

Nogueira, R., Yang, W., Cho, K., & Lin, J. (2019). *Multi-Stage Document Ranking with BERT* (arXiv:1910.14424). arXiv. http://arxiv.org/abs/1910.14424

Nosratabadi, S., Zahed, R. K., Ponkratov, V. V., & Kostyrin, E. V. (2022). Artificial Intelligence Models and Employee Lifecycle Management: A Systematic Literature Review. *Organizacija*, *55*(3), 181–198. https://doi.org/10.2478/orga-2022-0012

Osman, C.-C. (2019). Robotic Process Automation: Lessons Learned from Case Studies. *Informatica Economica*, *23*(4/2019), 66–71. https://doi.org/10.12948/issn14531305/23.4.2019.06

Ousterhout, J. K. (1998). *Scripting: Higher- Level Programming for the 21st Century*. Stanford University. https://web.stanford.edu/~ouster/cgi-bin/papers/scripting.pdf

Park, H., & Choi, S. O. (2019). Digital Innovation Adoption and Its Economic Impact Focused on Path Analysis at National Level. *Journal of Open Innovation: Technology, Market, and Complexity*, *5*(3), 56. https://doi.org/10.3390/joitmc5030056

Pereira, V., Munjal, S., & Ishizaka, A. (2019). Outsourcing and offshoring decision making and its implications for businesses—A synthesis of research pursuing five pertinent questions. *Journal of Business Research*, *103*, 348–355. https://doi.org/10.1016/j.jbusres.2019.07.009

Piatanesi, B., & Arauzo-Carod, J. (2019). Backshoring and nearshoring: An overview. *Growth and Change*, *50*(3), 806–823. https://doi.org/10.1111/grow.12316

Pradhan, S. (2017). Analysis of Impact Sourcing by Infusing Social Innovation in Outsourcing for Nepal. In J. Choudrie, M. S. Islam, F. Wahid, J. M. Bass, & J. E. Priyatma (Eds.), *Information and Communication Technologies for Development* (Vol. 504, pp. 829–834). Springer International Publishing. https://doi.org/10.1007/978-3-319-59111-7_69

Presbitero, A., & Teng-Calleja, M. (2022). Job attitudes and career behaviors relating to employees' perceived incorporation of artificial intelligence in the workplace: A career self-management perspective. *Personnel Review*, *52*(4), 1169–1187. https://doi.org/10.1108/PR-02-2021-0103

PwC. (2021). *Global Business Services (GBS) – Key to agility* (Global Business Services, p. 56) [Survey]. PWCIL. https://www.pwc.com/sk/sk/assets/PDFs/pwc-gbs2021-key-to-agility.pdf

PwC. (2023). *Global Business Services: Wertschöpfung und Erfolg im dynamischen Umfeld neu definieren PwC-Studie 2023: Ergebnisse unserer internationalen Kundenbefragung zu Themen rund um Global Business Services und deren aktuellen Herausforderungen.* (p. 79) [Survey]. PWCIL. https://www.pwc.de/de/prozessoptimierung/global-business-services-wertschoepfung-und-erfolg-im-dynamischen-umfeld-neu-definieren.html

Reyes, C. L. (2021). Autonomous Business Reality. *Southern Methodist University - Dedman School of Law*, *21*, 54.

Ribeiro, M., Singh, S., & Guestrin, C. (2016). *``Why Should I Trust You?'': Explaining the Predictions of Any Classifier*.

Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, *1*(5), 206–215. https://doi.org/10.1038/s42256-019-0048-x

Russell, S. J., Norvig, P., Chang, M., Devlin, J., Dragan, A., Forsyth, D., Goodfellow, I., Malik, J., Mansinghka, V., Pearl, J., & Wooldridge, M. J. (2022). *Artificial intelligence: A modern approach* (Fourth edition, global edition). Pearson.

Safar, S. (2021). Generative models for irregular sequential data. *Aalto University*, *55*. https://urn.fi/URN:NBN:fi:aalto-202108298599

Searle, J. R. (1980). Minds, brains, and programs. *THE BEHAVIORAL AND BRAIN SCIENCES*.

Sheikh, H., Prins, C., & Schrijvers, E. (2023a). *Mission AI: The New System Technology*. Springer International Publishing. https://doi.org/10.1007/978-3-031-21448-6

Sheikh, H., Prins, C., & Schrijvers, E. (2023b). *Mission AI: The New System Technology*. Springer International Publishing. https://doi.org/10.1007/978-3-031-21448-6

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, K., Graepel, T., & Hassabis, D. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature*, *529*(7587), 484–489. https://doi.org/10.1038/nature16961

Slepniov, D., Brazinskas, S., & Vejrum Wæhrens, B. (2013). Nearshoring practices: An exploratory study of Scandinavian manufacturers and Lithuanian vendor firms. *Baltic Journal of Management*, *8*(1), 5–26. https://doi.org/10.1108/17465261311291632

Sobczak, A., & Ziora, L. (2021). The Use of Robotic Process Automation (RPA) as an Element of Smart City Implementation: A Case Study of Electricity Billing Document Management at Bydgoszcz City Hall. *Energies*, *14*(16), 5191. https://doi.org/10.3390/en14165191

Spreitzenbarth, J., Stuckenschmidt, H., & Bode, C. (2021). *The state of artificial intelligence procurement versus sales and marketing*. https://doi.org/10.15480/882.3990

Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly*, *36*(2), 368–383. https://doi.org/10.1016/j.giq.2018.09.008

Tikkinen-Piri, C., Rohunen, A., & Markkula, J. (2018). EU General Data Protection Regulation: Changes and implications for personal data collecting companies. *Computer Law & Security Review*, *34*(1), 134–153. https://doi.org/10.1016/j.clsr.2017.05.015

Tong, S., Jia, N., Luo, X., & Fang, Z. (2021). The Janus face of artificial intelligence feedback: Deployment versus disclosure effects on employee performance. *Strategic Management Journal*, *42*(9), 1600–1631. https://doi.org/10.1002/smj.3322

Torre, G. (2017). Expectations versus Reality of Artificial Intelligence: Using Art to Examine Ontological Issues. *Leonardo*, *50*(1), 31–35. https://doi.org/10.1162/LEON_a_01342

Töytäri, P., Turunen, T., Klein, M., Eloranta, V., Biehl, S., & Rajala, R. (2018). Aligning the Mindset and Capabilities within a Business Network for Successful Adoption of Smart Services. *Journal of Product Innovation Management*, *35*(5), 763–779. https://doi.org/10.1111/jpim.12462

Turing, A. M. (1950). Computing Machinery and Intelligence. *Mind*, *59*(236), 433–460.

Ukor, R., & Carpenter, A. (2012). Service selection and horizontal multi-sourcing in process-oriented capability outsourcing. *Journal of Software: Evolution and Process*, *24*(3), 259–283. https://doi.org/10.1002/smr.557

Willcocks, L., Lacity, M., & Craig, A. (2017). Robotic Process Automation: Strategic Transformation Lever for Global Business Services? *Journal of Information Technology Teaching Cases*, *7*(1), 17–28. https://doi.org/10.1057/s41266-016-0016-9

Wirtz, B. (2022). Artificial Intelligence. In *Multi-Channel-Marketing*. Springer Gabler. https://doi.org/10.1007/978-3-658-03345-3_13

Wirtz, J., & Ehret, M. (2009). Creative restruction – how business services drive economic evolution. *European Business Review*, *21*(4), 380–394. https://doi.org/10.1108/09555340910970463

Wirtz, J., Tuzovic, S., & Ehret, M. (2015). Global business services: Increasing specialization and integration of the world economy as drivers of economic growth. *Journal of Service Management*, *26*(4), 565–587. https://doi.org/10.1108/JOSM-01-2015-0024

Wuest, T., Weimer, D., Irgens, C., & Thoben, K.-D. (2016). Machine learning in manufacturing: Advantages, challenges, and applications. *Production & Manufacturing Research*, *4*(1), 23–45. https://doi.org/10.1080/21693277.2016.1192517

Zaib, M., Sheng, Q. Z., & Emma Zhang, W. (2020). A Short Survey of Pre-trained Language Models for Conversational AI-A New Age in NLP. *Proceedings of the Australasian Computer Science Week Multiconference*, 1–4. https://doi.org/10.1145/3373017.3373028

Zhu, K., Kraemer, K. L., & Xu, S. (2006). The Process of Innovation Assimilation by Firms in Different Countries: A Technology Diffusion Perspective on E-Business. *Management Science*, *52*(10), 1557–1576. https://doi.org/10.1287/mnsc.1050.0487

Ziegler, D. M., Stiennon, N., Wu, J., Brown, T. B., Radford, A., Amodei, D., Christiano, P., & Irving, G. (2020). *Fine-Tuning Language Models from Human Preferences* (arXiv:1909.08593). arXiv. http://arxiv.org/abs/1909.08593

Websites and Statistics

Anand, S. (2022, June 6). *LinkedIn*. Retrieved November 5, 2023, from Evolving from Shared Services to Global Business Service.: https://www.linkedin.com/pulse/evolving-from-shared-services-global-business-service-saurav-anand/

Anyoha, R. (28. August 2017). *Harvard University*. Abgerufen am 5. November 2023 von The History of Artificial Intelligence: https://sitn.hms.harvard.edu/flash/2017/history-artificial-intelligence/

Aron, R., & Singh, J. V. (5. December 2005). *Harvard Business Review*. Abgerufen am 10. October 2023 von Getting Offshoring Right: https://hbr.org/2005/12/getting-offshoring-right

Böckeler, B. (November. 29 2023). *MartinFolwer.com*. Abgerufen am 4. December 2023 von Exploring Generative AI: https://martinfowler.com/articles/exploring-gen-ai.html

Barjatiya, P. (8. September 2023). *Medium*. Abgerufen am 14. December 2023 von The Impact of Large Language Models on Big Data Ingestion, Data Lakes, and Data Warehousing: https://pratikbarjatya.medium.com/the-impact-of-large-language-models-on-big-data-ingestion-data-lakes-and-data-warehousing-50a67a1ae78e

Becker, P. (29. November 2019). *Digital Business Cloud*. Abgerufen am 5. November 2023 von Robotic Process Automation: Digitale Transformation erfordert Automatisierung: https://www.digitalbusiness-cloud.de/robotic-process-automation-digitale-transformation-erfordert-automatisierung/

Bendor-Samuel, P. (13. February 2023). *Forbes*. Abgerufen am 5. November 2023 von Dilemma For Companies With GBS Centers And Software-Defined Operating Platforms:

https://www.forbes.com/sites/peterbendorsamuel/2023/02/13/dilemma-for-companies-with-gbs-centers-and-software-defined-operating-platforms/?sh=10189cf91328

Brown, S. (2021, April 21). *MIT – Managment Sloan School*. Retrieved November 2023, from Machine Learning, explained: https://mitsloan.mit.edu/ideas-made-to-matter/machine-learning-explained

Bryan, J. (22. Ferbuary 2019). *Gartner*. Abgerufen am 5. November 2023 von 5 Characteristics of the Best Shared Services Centers: https://www.gartner.com/smarterwithgartner/five-characteristics-of-the-best-shared-service-centers

Dilmegani, C. (9. May 2023). *AI Multiple*. Abgerufen am 9. November 2023 von State of RPA vs RDA in 2023: Main 4 Differences: https://research.aimultiple.com/rpa-vs-rda/

Economic Times. (8. January 2020). *AI Software Market to reach $126 billion in 2025.* (ETGovernment, Hrsg.) Abgerufen am 4. December 2023 von Economic Times Government: https://government.economictimes.indiatimes.com/news/technology/ai-software-market-to-reach-126-billion-by-2025/73148640

Eddy, D. (1. May 2019). *UiPath*. Abgerufen am 12. December 2023 von How RPA Transforms Data Migration: https://www.uipath.com/blog/rpa/how-rpa-transforms-data-migration

Endrizzi, S. (23. October 2023). *Forbes*. Abgerufen am 24. December 2023 von How AI Can Impact COmpanies: https://www.forbes.com/sites/forbesbusinesscouncil/2023/10/23/how-ai-can-impact-companies/?sh=56ec57333817

Forbes. (25. April 2023). *Forbes*. Abgerufen am 4. October 2023 von 24 Top AI Statistics And Trends In 2024: https://www.forbes.com/advisor/business/ai-statistics/

GEP. (27. September 2023). Abgerufen am 14. October 2023 von GEP: DECODING AI'S TRANSFORMATIVE IMPACT ON SOURCE-TO-PAY AND PROCURE-TO-PAY

Goldman Sachs. (March 2023). *Statista.* Abgerufen am 4. October 2023 von Industry employment at risk of automation by artificial intelligence (AI) in the Euro area: https://www.statista.com/study/38609/artificial-intelligence-ai-statista-dossier/

Gupta, S., & Fersht, P. (21. August 2023). *HorsesforSources*. Abgerufen am 8. October 2023 von GBS (Global Business Services) is dead. Long live GBS (Generative Business Services): https://www.horsesforsources.com/gbs-is-dead-long-live-gbs_082123/

Hintze, A. (14. November 2016). *The Conversation*. (Michigan State University) Abgerufen am November 2023 von Understanding the four types of AI, from reactive robots to self-aware beings: https://theconversation.com/understanding-the-four-types-of-ai-from-reactive-robots-to-self-aware-beings-67616

Hodge, B. (2020, February 19). *5 Reasons GBS Adds Value to the Digital Enterprise*. Retrieved October 04, 2023, from 2020's most popular target operating model: https://www.ssonetwork.com/global-business-services/articles/5-reasons-gbs-adds-value-to-the-digital-enterprise

Howells, K. (5. July 2023). *HR Grapevine*. Abgerufen am 31. December 2023 von Displacement | Younger workers are terrified that AI will make them redundant - here's what to tell them: https://www.hrgrapevine.com/content/article/2023-07-04-younger-workers-are-terrified-that-ai-will-make-them-redundant-heres-what-to-tell-them

Jesse, M. (2023). *Almato*. Von Robotic Process Automation (Unattended Automation) vs. Robotic Desktop Automation (Attended Automation): https://www.almato.com/blog/rpa-vs-rda/ abgerufen

Jones, S. (2020, March 10). *Celonis*. Retrieved from What Is Hyperautomation: What's the Hype All About?: https://wwwhttps://www.celonis.com/blog/hyperautomation-whats-the-hype-all-about/?creative=&keyword=&matchtype=&network=x&device=c&gad_source=1&gclid=CjwKCAiA4smsBhAEEiwAO6DEjbOjlz.rinf.tech/top-6-hyperautomation-trends-that-will-shape-the-market-in-2023/

Joshi, N. (19. June 2019). *Forbes*. (Cognitive World) Abgerufen am November 2023 von 7 Types Of Artificial Intelligence: https://www.forbes.com/sites/cognitiveworld/2019/06/19/7-types-of-artificial-intelligence/?sh=64585993233e

Lareo, X. (12. December 2023). *EUROPEAN DATA PROTECTION SUPERVISOR*. Abgerufen am 15. December 2023 von Large language models (LLM): https://edps.europa.eu/data-protection/technology-monitoring/techsonar/large-language-models-llm_en#:~:text=Moreover%2C%20if%20not%20properly%20secured,potential%20or%20real%20data%20breaches.&text=LLMs%20sometimes%20suffer%20from%20so,that%20appears%20to

Marr, B. (7. July 2021a). *Bernard Marr & Co.* Abgerufen am November 2023 von What are the Four Types of AI?: https://bernardmarr.com/what-are-the-four-types-of-ai/

Marr, B. (2. June 2021b). *Bernard Marr & Co.* Abgerufen am November 2023 von What is Weak (Narrow) AI? Here Are 8 Practical Examples: https://bernardmarr.com/what-is-weak-narrow-ai-here-are-8-practical-examples/

McKinsey. (March 2023). *Statista.* Abgerufen am 5. October 2023 von Influence of generative artificial intelligence (AI) on worldwide productivity growth: https://www.statista.com/study/38609/artificial-intelligence-ai-statista-dossier/

Murphy, J. (28. April 2023). *TechTarget*. Abgerufen am 05. November 2023 von How businesses can measure AI success with KPIs: https://www.techtarget.com/searchenterpriseai/tip/How-businesses-can-measure-AI-success-with-KPIs

Next Move Strategy Consulting. (22. March 2023). *Statista.* Abgerufen am 3. November 2023 von Global artificial intelligence market size 2021-2030: https://www.statista.com/study/38609/artificial-intelligence-ai-statista-dossier/

Peatman, B. (20. October 2022). *piralto*. Abgerufen am 29. October 2023 von The Difference Between Offshoring vs. Outsourcing: https://www.prialto.com/blog/offshoring-vs-outsourcing#:~:text=Offshoring%20and%20outsourcing%20are%20often,business%20operations%20in%20another%20country

Pichai, S. (17. April 2023). *Fortune*. Von Alphabet CEO Sundar Pichai says that A.I. could be 'more profound' than both fire and electricity—but he's been saying the same thing for years: https://fortune.com/2023/04/17/sundar-pichai-a-i-more-profound-than-fire-electricity/# abgerufen

Raidops. (March 2023). *Raidops*. Abgerufen am December 2023 von 25 Best Generative AI Tools: The Power and Pressure Game Is On!: https://www.rapidops.com/blog/generative-ai-tools/

Reid, E. (10. May 2023). *Google – The Keyword*. Abgerufen am 01. January 2024 von Supercharging Search with generative AI: https://blog.google/products/search/generative-ai-search/

Rose, J. (28. Juni 2023). *The Blue AI*. Abgerufen am 5. November 2023 von GenAI-Modelle: Generierung von Inhalten mit KI: https://theblue.ai/blog-de/genai-modelle/

Sagawa, C. (24. July 2022). *Day.io*. Abgerufen am 5. November 2023 von GLobal Business Services (GBS): What are they?: https://day.io/blog/global-business-services-gbs-what-are-they/#:~:text=Difference%20between%20GBS%20and%20SSC&text=SSCs%20tend%20to%20focus%20on,facing%20and%20back%2Doffice%20operations.

Saha, D. (17. August 2023). *Forbes*. Abgerufen am 10. October 2023 von Navigating Change Management In The Era Of Generative AI: https://www.forbes.com/sites/forbestechcouncil/2023/08/17/navigating-change-management-in-the-era-of-generative-ai/

Siemens. (2023). *Siemens*. Abgerufen am 14. December 2023 von Generative AI and a new era of business transformation: https://www.siemens.com/global/en/products/services/gbs/our-insights/newsroom/generative-ai.html

Siyong, L. (21. April 2018). *Medium*. Abgerufen am 5. November 2023 von The Difference between Robotic Process Automation and Artificial Intelligence: https://cfb-bots.medium.com/the-difference-between-robotic-process-automation-and-artificial-intelligence-4a71b4834788

Stanford University. (2022). *Statista.* Retrieved October 4, 2023, from Global private investment in AI 2022, by industry: https://www.statista.com/study/38609/artificial-intelligence-ai-statista-dossier/

Stanford University. (2023, March 22). *Statista.* Retrieved from Global corporate artificial intelligence (AI) investments: https://www.statista.com/study/38609/artificial-intelligence-ai-statista-dossier/

Statista. (2023, Dec 18). *Statista*. Retrieved Dec 20, 2023, from Artificial intelligence (AI) worldwide - statistics & facts: https://www.statista.com/topics/3104/artificial-intelligence-ai-worldwide/#topicOverview

Uhura. (08. August 2023). *Uhura Solutions*. Abgerufen am 12. December 2023 von Streamlining Invoice Processing with AI: https://uhurasolutions.com/2023/08/08/streamlining-invoice-processing-with-ai/

Zenonos, A. (20. January 2023). *Medium*. Abgerufen am 14. October 2023 von Data Regulations in the EU, China and US: https://medium.com/geekculture/data-regulations-in-the-eu-china-and-us-44a2073af3a0

Statement of Independence

I hereby declare that this thesis, titled “AI for GBS: Experiences, Use Cases, and Implementation” is the result of my own original research and that it has not been submitted in any form for another degree or qualification to any other university or institution. All sources and references used in this thesis have been duly acknowledged and cited.

I affirm that the work presented in this thesis is free from any form of plagiarism. I have taken care to ensure that the ideas, theories, and findings of others are properly credited through citations and references. Any text or idea borrowed from external sources is clearly identified and acknowledged in the text.

Furthermore, I assert that I have not received any unauthorized assistance or collaboration in the preparation of this thesis. The intellectual content and conclusions presented herein are the product of my own efforts and critical thinking.

I acknowledge that any breach of academic integrity, including plagiarism or misrepresentation, may result in severe consequences, including the cancellation of the degree for which this thesis is being submitted.

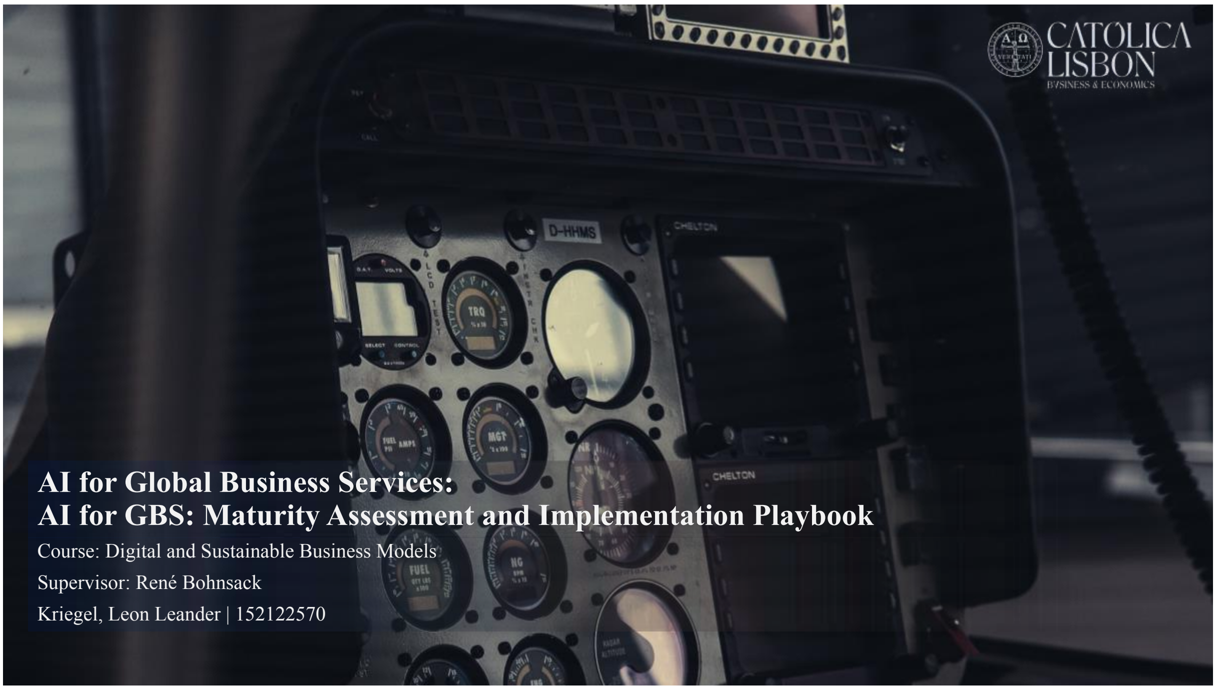
By affixing my signature below, I confirm that this Statement of Independence accurately represents my commitment to academic integrity and the authenticity of the work presented in this thesis.

	Hamburg, 03.01.2024
Kriegel, Leon Leander	Location, Date

Appendix

Appendix I: Maturity Assessment and Implementation Playbook

This AI for GBS maturity assessment and implementation playbook outlines specific approach for the implementation of AI into GBS units. It was based on several publications (to be found on the according slides) and should guide executives through the key different steps of defining a GBS strategy.



Management Summary

This AI implementation blueprint **highlights the critical considerations** for advancing AI readiness within a Global Business Services (GBS) entity. Starting with an examination of the GBS's political structure, the emphasis is on securing autonomy for effective technology integration. Developing a GBS-specific strategy encompasses technological and employment aspects, crucial for fostering a technology-savvy mindset among employees. Recommendations include the formation of a task force for use case analysis and infrastructural possibilities, particularly focusing on data security and harmonization. The significance of geographical location for data security, the alignment of the technology stack with the digital strategy, and the implementation of a dedicated change management program are pivotal for successful AI integration. Finally, the establishment of measurable KPIs is crucial for evaluating the effectiveness of AI implementation, ensuring a comprehensive assessment of process efficiency, cost savings, and error susceptibility. The roadmap presented sets the stage for the subsequent chapter, which delves into the analysis of specific use cases for the AI task force.

Reach GBS sovereignty → **Build tech-savy mindset** → **Establish GBS specific AI unit** → **Use case identification** → **Data harmoni-sation** → **Define a change management program** → **Set-up measures & KPIs** (pre/post AI) → **Tool selection and implemen-tation**

This playbook is designed for decision-makers, equivalent to C-level executives. It focuses on functional aspects such as Governance, Data & Technology, Regulatory compliance, rather than financial metrics like ROI. It will lead you through the entire process, offering a high-level overview from the current stage to the completion of change management.

Roadmap overview – AI for GBS

Starting Point

Questions

- *Is my GBS **ready** for AI?*
- *How can a GBS **attract** and find tech-savvy talent?*
- *Which topics do we need to be **aware** of when utilizing AI?*
- *What are use cases/ success stories of AI **implemented** into GBS?*
- *What **differentiates** GBSs from other organization units?*

Maturity Questionnaire

Questions

- *When implementing AI, how guaranteed is it to stay compliant?*
- *What are the regulatory requirements?*
- *Do we fulfil the technical prerequisites for such a project?*
- *How costly will be undertaking the projects we consider?*
- *What impact will it have on productivity, culture and processes?*

Technology Selection

Questions

- *What risks do we have to undertake conducting a project?*
- *Do we have the right talent/people internally to undertake an AI project?*
- *Which skills and prior knowledge are required by the selected project(s)?*
- ***Result:** Project Selection Template (Out of Scope)*

Scoring and Classification

Questions

- *How is the maturity of our GBS compared to others?*
- *Where are the low-hanging fruits in terms of optimization potentials?*
- *Where can AI support improving our operative business?*

***Result:** Decision template*

Implementation Roadmap

Questions

- *How does the implementation Roadmap look like?*
- *Which departments do we have to consider?*
- *What is the length of the selected project(s)?*
- ***Result:** Implementation Playbook*

Change Management

Questions

- *Do our employees need to be trained to work with the new solution?*
- *Who will be the responsible contact for our new solution?*
- ***Result:** Project/ Solution Handbook*

Existing literature describes how to develop an "AI strategy". This model describes a hands-on approach how to implement AI into a Global Business Unit in order to become an accelerator for human capital and reach a techy skill sets among your employees.

X

Step 1: The Starting Point

CATOLICA LISBON

Reach GBS sovereignty → Build tech-savy mindset → Establish GBS specific AI unit → Use case identification → Data harmoni-sation → Define a change management program → Set-up measures & KPIs (pre/post AI) → Tool selection and implemen-tation

Today's Strategy

- Within your company's strategy are there any requirements that must be considered before undertaking a new project, e.g.:
  - Sustainability
  - Compliance
  - Geo-political aspects (e.g. coopoerations within EU only)
- What are you company's annual targets? (e.g. reduce cost, increase # of emplyees)

Problems

- Where exactly are bottlenecks, inefficient process steps or blockages in automation?
- What is the first thing that comes to mind when you think of "problematic process steps"?
- Is there a lot of optimisation potential in the same department? Are they evenly distributed?

Objectives and Expectations

- What is to be solved/achieved with the help of AI?
- What are your expectations of the project?
- What must AI be able to do for you?

Cost & Impact

- Is there already a defined budget for the project?
- If the project is successfully implemented, how big is the impact?
- Is there a cost-benefit key according to which projects are implemented in your company?

Analyse at which part of the above shown process your GBS is right now. Derive further initiatives.

02.01.24 AI for GBS: Pre-Project Assessment and Implementation Playbook Sources: Turing (2023) 4

Step 2: Maturity Questionnaire – Categories Evaluated

Microsoft Excel Worksheet

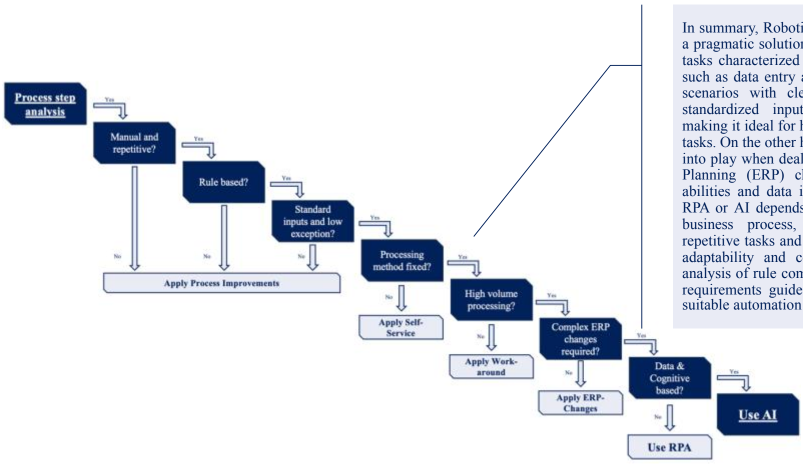
CATOLICA LISBON

Strategic Vision	A well-defined AI strategy is paramount for GBS AI readiness, aligning business objectives with AI initiatives. It provides a **roadmap for effective deployment**, ensuring that AI applications contribute directly to corporate goals and fostering a clear sense of purpose in AI adoption within the GBS.
Data	Data is the lifeblood of AI, and the Data dimension focuses on harnessing the power of data for optimal AI performance. A well-crafted data strategy, encompassing security, quality, and accessibility considerations, ensures a solid foundation for AI applications. Successful AI integration in a GBS is contingent on mastering the dynamics of data utilization.
Technology	Technology forms the backbone of AI integration in a GBS. A robust technological infrastructure, equipped with scalable and advanced tools, is necessary for seamless AI operations. The Technology dimension ensures that the GBS possesses the necessary computational power, storage capacity, and tools to support diverse AI applications.
People & Talent	The People & Change dimension is crucial as it focuses on **developing the necessary human capital** for successful AI integration. Cultivating a culture that embraces change, invests in continuous learning, and attracts and retains AI talent is essential to harness the full potential of AI within the GBS
Governance & Compliance	Governance & Compliance ensures **responsible and ethical AI practices** within the GBS. It establishes the frameworks to navigate legal and regulatory landscapes, safeguard data privacy, and maintain compliance. Robust governance is foundational for building trust in AI applications and sustaining long-term success.

Achieving optimal AI readiness within a GBS demands a strategic vision, a dynamic culture fostering continuous learning, robust governance and compliance practices, state-of-the-art technological foundations, and a mastery of data dynamics to unleash the full potential of artificial intelligence across operations.

02.01.2024 AI for GBS: Pre-Project Assessment and Implementation Playbook Sources: IBM (2021); AWS (2022); MMC Ventures (n.d.) 5

Step 3: Technology Selection: AI vs. RPA



In summary, Robotic Process Automation (RPA) serves as a pragmatic solution for automating manual and repetitive tasks characterized by routine and rule-based operations, such as data entry and invoice processing. RPA excels in scenarios with clearly defined rules, structured data, standardized inputs, and fixed processing methods, making it ideal for high-volume, repetitive data processing tasks. On the other hand, Artificial Intelligence (AI) comes into play when dealing with complex Enterprise Resource Planning (ERP) changes or tasks requiring cognitive abilities and data interpretation. The decision to deploy RPA or AI depends on the specific characteristics of the business process, with RPA suited for rule-based, repetitive tasks and AI preferred for processes demanding adaptability and cognitive interpretation. A thoughtful analysis of rule complexity, data variability, and cognitive requirements guides organizations in selecting the most suitable automation solution for optimal efficiency.

Select the right technology according to the process shown. Do not implement AI for the sake of implementing AI. With RPA many Use Cases can be realized.

Step 4: Score Card and Classification

Description

- The heatmap will have the following categories to be evaluated:
  - Strategic Vision
  - Data & Technology
  - Governance
  - Compliance
  - People & Talent
  - Budgeting
  - Impact
- Derived from the scoring, use case and the GBS's maturity status the AI Model selection follows (LLM, ORC etc..)

Scoring

- .Scoring determines the usefulness of an AI implementation
- It evaluates the use case according to its utilisation and the general situation of the company
- Based on the values specified in the Maturity Questionnaire, the scoring awards a score on a scale of -100 to 100 points.
- It goes both ways, as it can also have negative effects on a company (e.g. dilution of the company culture)

-100 100

Project Matrix

- The starting point x is at the position (0|0)
- The axes represent the following value groups:
  - X1-axis: Urgency (The urgency with which the solution is needed.)
  - X2-axis: Effort (The effort required to maintain the solution)
  - Y1-axis: Impact (What will be the impact of the initiative (people, technology, processes, culture, etc.)?
  - Y2-axis: Costs (What are the expected costs of the project?)

Classification and Recommendation

- According to the enhanced Eisenhower Matrix, the four quadrants sort the projects in “Investigate”, “Prioritize”, “Avoid” and “Consider”
- Classification in Light- , Medium, Hard Case depending on the points reached of each individual project
- Recommendation on priorization according to the maturity per category

…

Step 5: Implementation Blueprint

Idea ▶ Research ▶ Prototype ▶ MVP ▶ **Production**

Prototype → Research

Production → Idea Features ▲ R&D ▲ QA ▲ Production

The implementation approach involves progressing from conceiving an idea to delivering a fully realized product. It begins with brainstorming and market analysis to formulate a clear vision. In-depth research follows to validate the idea and understand market dynamics. A prototype is then developed for visualization, leading to the creation of a Minimum Viable Product (MVP) released for user feedback. Full-scale production, feature enhancements, and continuous research and development (R&D) are undertaken based on iterative improvements and emerging technologies. Rigorous Quality Assurance (QA) ensures reliability and security throughout the development life cycle. This structured approach allows for flexibility, incorporating user feedback and staying competitive in the market.

…

Sources: MMC Ventures

Step 6: Change Management

Training and Enablement

- Within your **company's employment strategy** are there any internal requirements that must be considered before undertaking a new project, e.g.:
  - Sustainability
  - Compliance
  - Geo-political aspects (e.g. coopoerations within EU only)
- What are your company's annual targets? (e.g. reduce cost, increase the number of emplyees)

Responsibility and Contacts

- Definition of a **Change Management Agent**, having the responsibility during the whole transition phase
- **Post-implementation responsibility** to a single person (SPOC; comparable to a Product Owner)

Result: Project Handbook

- **Training materials** for AI basics (understandable for people without an IT background)
- **Click instructions** or compare instructions for use
- Summary of current initiatives
- Auditable implementation (governance)
- Traceability and verifiability of activities for warranties
- AI team governance chart (hierarchy)
- Definition of KPIs and measures to measure the concrete impact

The handbook is stored as a PDF signed by the project management and can be accessed and viewed centrally by authorised persons.

Sources: Harvard Business School Online (2020), Mukthar et al. (2022)

Appendix II: Interview Outlines and Transcripts

As described in chapter 3. Methods, ten qualitative expert interviews were conducted to validate the maturity status and assumptions regarding the specific implementation of AI into GBS. The "main questions" (1.-13.) can be found below and were adjusted to the individual backgrounds and profile of the interviewees. The transcripts are attached as document. To code, MAXQDA was used. The corresponding codes and the process step can be taken from Appendix IV.

Transcriptions

All transcripts can be found here:

AI for GBS - All Transcriptions.doc

Outline

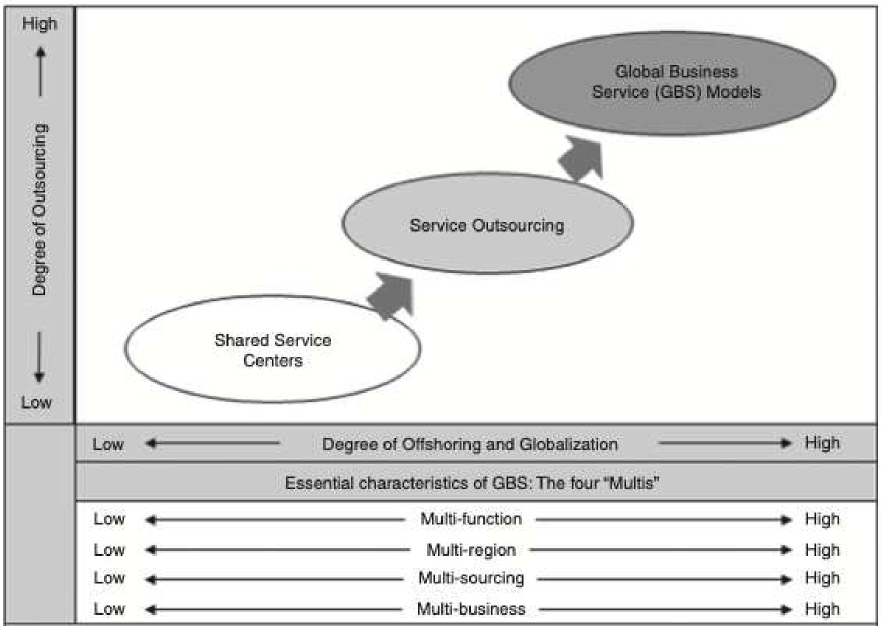
1. *What is your age, position and since when are you working at Nebula GBS?*
2. *Which prior knowledge do you have using AI? Are you generally interested in AI?*
3. *What do you relate with AI? Do you see it as a chance? Do you fear the future with AI?*
4. *Do you know about any AI initiatives within Nebula GBS? Are you in contact with AI in your job?*
5. *What challenges or opportunities do you foresee in adopting new AI technologies?*
6. *Do you know about problems/issues/bottlenecks in the processes you are working in? Do you think that AI could assist there?*
7. *Are you dealing with large amounts of data in your job? What is the current state of data quality and availability?*
8. *What mechanisms are in place for monitoring and evaluating general performance?*
9. *How do you "learn" at Nebula GBS?*
10. *From your perspective, what make GBS processes different from e.g. medium-sized enterprises?*
11. *How is the workforce currently prepared for AI integration within GBS?*
12. *Are there ongoing training programs for employees to enhance AI-related skills?*
13. *Can you share insights into the organizational culture related to technological change?*

Appendix III: The evolution of Global Business Services

The model according to Wirtz et al. (2015) showed below, represents the theoretical model used to investigate on the status of GBS development with parallel development of emerging technology. The authors pinpointed that there are large differences between SSCs and GBS models in many dimensions such as scope, agility, governance etc.

Global business services

573



Key dimensions of fully integrated GBS models

Dimension	Shared Service Centers (domestic and offshore)	Service Outsourcing (domestic and offshore)	Gobal Business Services (GBS)
Typical objectives	Cost saving, improved efficiencies and capabilities	Cost savings, efficiencies, compliance, agility, and scalability	Cost savings, efficiencies, compliance, service focus, agility, scalability, and innovation
Scope	Typically 1 to 2 non-core processes, may include critical business processes	Typically 1 to 2 non-core processes; 1 or more providers; Typically does not include critical business processes	Many processes and many providers; combination of shared services and outsourcing/offshoring; not just transactional activities; includes also critical business processes
Agility	Agile as it relates to in-scope processes	Limited by the scope of the contract with provider	High, because coordinated certrally
Governance	Variety of approaches ranging from siloed to coordinated	Frequently managed as separate contracts with each external provider	Certralized and coordinated
Culture	Practice is to establish a service-focused culture	Typically approached as managing a third-party contract	Transformational change; Service-focused culture is fundamental; work as a single team regardless of shared services or outsourcing

Figure 6.
The evolution and key dimensions of global business services models

Appendix IV: Interview Coding Table

The codes in this table were used to analyse the qualitative interviews underlying the empirical study of this thesis. The analysis was conducted according to Mayring (2000;2010).

Code title	Type	Code Question	# found	Introduced at
1. Strategy Vision	**Code**	What incorporates the (Digital) Strategic Vision of the GBS	**82**	0%
1.1 Unique GBS attributes	Sub-Code	What differentiates GBS from other organisational units.	()	30%
1.2 Company Background	Sub-Code	Recent strategic development or development history. How did the company came to the current status?	()	30%
1.3 GBS Organization	Sub-Code	How is the GBS organised?	()	30%
2. People, Talent & Change	**Code**	Who do you learn at GBS? What talent is employed? Which backgrounds are common?	**51**	0%
2.1 GBS Culture	Sub-Code	How do you work at the GBS?	()	30%
2.2 Change Management	Sub-Code	What is changing in which way recently?	()	30%
2.3 Prior Knowledge AI	Sub-Code	*Merged with "F. Opening" after 30%*	n/a	30%
3. Technology	**Code**	Which tools and technology are used?	**64**	0%
4. Data	**Code**	How is the current data quality?	**11**	0%
5. Process	**Code**	How can the processes be described?	**29**	0%
5.1 Hire-to-retire	Sub-Code	What describes the H2R process?	()	30%
5.2 Travel and Expenses	Sub-Code	What describes the T&E process?	()	30%
5.3 Source-to-pay	Sub-Code	*Merged with "5. Processes" at 100%.*	n/a	30%
6. Regulatory, Governance & Compliance	**Code**	What are external and internal regulatory requirements that need to comply with?	**39**	0%
6.1 Corporate Governance	Sub-Code	How do the internal governance structures look like?	()	30%
A. Ideas, Suggestions & Opportunities	**Code**	What are opportunities, ideas and suggestions regarding the implementation of AI?	**135**	0%
B. Challenges & Risks	**Code**	What are risks and challenges regarding the implementation of AI?	**96**	0%
C. Blocker	**Code**	What are (potential) blockers regarding the implementation of AI?	**29**	30%
D. Closing	**Code**	Everything after the last pre-defined interview question.	**18**	30%
E. Interviewer speaks	**Code**	This part shows when the interviewer speaks.	**227**	0%
F. Opening	**Code**	What is you background and education? How long have you been with Nebula ? Whats your position?	**19**	0%

Appendix V: AI for GBS Readiness Assessment

Find the Excel Version oft he Readiness Assessment here:

Wiki

Wiki	**1**	**Novice/Initial**	Limited AI adoption, lacks strategic alignment, and minimal skills; basic technology infrastructure is in place but lacks scalability.
	2	**Emerging/Developing**	Some alignment with business strategy, developing leadership and governance, moderate skills with ongoing training efforts, and a technology infrastructure in progress with limited scalability.
	3	**Intermediate/Established**	Reasonable alignment with business strategy, established leadership and governance structures, adequate skills with continuous training, and a moderately advanced and scalable technology infrastructure.
	4	**Advanced/Mature**	Strong alignment with business strategy, well-established leadership and governance, high-level skills with continuous training, and advanced, scalable technology infrastructure.
	5	**Leading/Exemplary**	Full alignment with business strategy, exceptional leadership and governance setting industry standards, highly skilled workforce with a culture of continuous learning, and cutting-edge, highly scalable technology infrastructure.
	0	**I don't know**	I don't know about the status.

Questionnaire

#	Questions	Category	Answer
1	How mature is the GBS in terms of data quality?	Data	**Intermediate/ Established**
2	Is there a well-defined data strategy for AI, including data sourcing, cleansing, and storage?	Data	**Emerging/ Developing**
3	How mature is the GBS in terms of data security?	Data	**Advanced/ Mature**

4	How mature is the GBS in terms of data accessibility?	Data	**Emerging/ Developing**
5	How mature is the GBS in terms of data harmonisation?	Data	**Intermediate/ Established**
6	How is AI governance structured, and are there established policies and guidelines?	Governance & Compliance	**Intermediate/ Established**
7	Are there efforts to automate routine tasks and enhance decision-making using AI?	Governance & Compliance	**Novice/Initial**
8	How is the GBS managing ethical considerations and potential risks associated with AI?	Governance & Compliance	**Emerging/ Developing**
9	Are there mechanisms in place to ensure compliance with relevant regulations?	Governance & Compliance	**Leading/ Exemplary**
10	To what extent does the GBS collaborate with external partners, vendors, or industry ecosystems for AI capabilities?	Governance & Compliance	**Emerging/ Developing**
11	Is there active participation in industry forums and knowledge-sharing platforms related to AI?	Governance & Compliance	**Novice/Initial**
12	How well is the GBS aligned with the overall business strategy regarding AI adoption?	People & Change	**Leading/ Exemplary**
13	Is there a dedicated leadership team responsible for driving AI initiatives within the GBS?	People & Change	**Intermediate/ Established**
14	Does the GBS have the necessary skills and expertise in AI technologies?	People & Change	**Emerging/ Developing**
15	Is there a continuous training program to keep the workforce updated on AI advancements?	People & Change	**Novice/Initial**
16	How is the GBS managing ethical considerations and potential risks associated with AI?	People & Change	**Novice/Initial**
17	Is there a culture of innovation that encourages experimentation and learning from AI implementations?	People & Change	**Leading/ Exemplary**
18	Is there plan of action for achieving the desired level of AI maturity in the organization.	Strategy	**Emerging/Developing**
19	To what extent is the AI implementation strategy aligned with the overall business strategy?	Strategy	**Advanced/Mature**
20	Does the organization have a clearly articulated long-term vision for integrating AI?	Strategy	**Intermediate/Established**
21	Are there clear objectives and goals for integrating AI within the GBS framework?	Strategy	**Novice/Initial**
22	To what extent are AI capabilities integrated into existing GBS processes?	Strategy	**Novice/Initial**
23	Are key performance indicators (KPIs) defined to assess the success of AI initiatives?	Strategy	**Emerging/Developing**
26	What is the current state of technology infrastructure supporting AI within the GBS?	Technology	**Intermediate/Established**
27	Is the infrastructure scalable and flexible to accommodate future AI developments?	Technology	**Novice/Initial**

28	To what degree is AI being utilized to enhance the customer experience within the GBS?	Technology	**Emerging/Developing**
29	How agile is the GBS in adopting new AI technologies and methodologies?	Technology	**Advanced/Mature**
30	Are there plans for implementing AI-driven improvements in customer service?	Technology	**Advanced/Mature**

Scoring Matrix

Category	Score	Classification	Recommendation
Strategy	**2,2**	**> 1,5**	***You are finding yourself in a very early stage of defining the strategy for the corresponding topic. Try to speak about the corresponding topic with experts within your company. At this stage, the GBS is taking its first steps toward AI integration, establishing essential elements to lay the groundwork for future advancements. Limited AI adoption, a nascent strategic alignment, and basic technology infrastructure characterize this initial phase.*** **Strategy:** Develop a clear AI strategy that aligns with overarching business objectives and identify specific use cases for AI deployment in GBS. **Technology:** Clarify policies of technology adoption. Are you allowed to adopt software besides the pre-determined one of your mother company? How flexible are you in your technology selection? **Data:** For the start, stick to your group policy regarding the data handling (security, acces and quality). Start developing a basic data strategy. Focus on data security and basic quality control. If applied this will take you to the next step. **People & Change:** Initiate basic training programs to raise awareness about AI and foster a culture of openness to change. Try to define an employee strategy and set up a GBS-Mindset for continuos improvement! Think about answering questions like: Which talent do you want to attract? What do they need to know regarding emerging technologies? Which skills do they need to have? **Governance & Compliance:** Establish basic governance mechanisms to ensure data privacy and compliance. Begin with clear policy development.
Technology	**2,8**	**1,5 – 2,49**	***Good start! You are either just established the GBS or fin yourself in the middle of a transformation. The GBS is in the process of enhancing its AI capabilities, demonstrating a growing alignment with business strategy. Leadership and governance are evolving, and moderate skills, coupled with ongoing training initiatives, signify a developing stage. The technology infrastructure is in progress but exhibits limited scalability.*** **Strategy:** Strengthen the alignment of the AI strategy with the business strategy by advancing leadership and governance. Focus on identifying new opportunities for AI applications. **Technology:** Invest in technology infrastructure for AI. Focus on fundamentals like scalability and integration OR expand your technology infrastructure to enable more scalability and flexibility. **Data:** Expand your data strategy by establishing clear guidelines for data quality and accessibility. Invest in basic data governance. **People & Change:** Intensify training initiatives to strengthen employees' AI competencies. Create incentives for continuous learning and promote an open attitude towards change. Think about Who can take over the tool implemented in the future? **Governance & Compliance:** Strengthen governance structures by defining clear responsibilities for data privacy and compliance. Implement regular audits and training.
Data	**2,8**	**2,5 – 3,49**	***In this phase, the GBS has achieved a reasonable alignment with its business strategy. Well-established leadership and governance structures are in place, supported by a skilled workforce undergoing continuous training. The technology infrastructure is moderately advanced and exhibits scalability.*** **First state of maturity is assesst in the corresponding category ...** **Strategy:** Refine the alignment of the AI strategy by continuously monitoring and adapting to the business strategy. Emphasize continuous improvement in AI utilization and identify avenues for further integration. **Technology:** Optimize existing technology investments to support advanced AI applications. Implement mechanisms for continuous technological advancement. Ask existing partners for extension options according to you defined use cases. **Data:** Optimize your data strategy through advanced data governance practices. Implement advanced technologies for data management and analysis. **People & Change:** Consolidate skills through targeted training programs and establish clear career paths for AI experts. Foster a culture of innovation and collaboration.

			Governance & Compliance: Optimize existing governance mechanisms and ensure regular updates to policies. Implement advanced compliance measures.
People & Change	**2,8**	**3,5 - 4,5**	***The GBS has reached an advanced stage, showcasing strong alignment with the business strategy. Leadership and governance are well-established, and the workforce possesses high-level skills with ongoing training initiatives. The technology infrastructure is advanced and scalable, reflecting a mature state of AI integration.*** **Strategy:** Strengthen the advanced alignment of the AI strategy by solidifying leadership and governance. Promote innovation and set clear goals for optimizing AI utilization. **Technology:** Solidify your advanced technology infrastructure by introducing innovative AI tools. Implement best practices for technological scalability. Research for cutting-edge technologies and build a highly scalable infrastructure. Be a pioneer in adopting new technologies. **Data:** Solidify your advanced data strategy by proactively aligning with innovative data solutions. Implement advanced methods for data analysis. Work on your AI Readiness of your data vailable. **People & Change:** Establish advanced training models to build a highly skilled AI team. Promote a positive culture of change where innovative ideas are valued. **Governance & Compliance:** Solidify governance structures by proactively aligning with future data privacy requirements. Establish advanced mechanisms for risk assessment. Set standards in governance and compliance. Actively contribute to shaping GBS industry-leading standards and take a leading role in compliance.
Governance & Compliance	**2,3**	**< 4,5**	***Excellent! Your reached a leading maturity state in GBS transformation. As a leader, focus on advancing your AI strategy by constantly integrating industry best practices. Invest in pioneering initiatives and advocate for the creation of industry standards. At the forefront of AI integration, the GBS exhibits full alignment with the business strategy. It sets industry standards with exceptional leadership and governance, a highly skilled workforce ingrained in a culture of continuous learning, and a cutting-edge, highly scalable technology infrastructure. This represents the epitome of AI excellence within the GBS.***

Radar chart according to the five dimensions