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Customer Perspective towards the Utilisation of Artificial Intelligence in Financial Services

Redisa C. Wibawa[a], Basuki Wibawa[b*], [a]Faculty of Accounting and Finance University of Aberdeen, [b]Faculty of Engineering Universitas Negeri Jakarta, Email: [a]t08rw18@abdn.ac.uk, [b*]bwibawa@unj.ac.id

The current focus of data processing has been through the revolutionary technology of Artificial Intelligence (AI); which can be interpreted as a way of training computers to mimic and simulate human thinking patterns and behaviours (Tecuci, 2012; Allam & Dhunny, 2019). The AI has become an important solution in producing accuracy and accountability to better understand the complexity of many issues in financial services. With the advancements of AI usage to adapt effectively with changing control environments and customer requirements, this paper aims to assess the customer perspective towards the utilisation of AI in financial services using the AI-driven Customer Experience Management theoretical framework by Gacanin and Wagner (2019). The paper is based on the practice-led case study between an accounting firm (PwC) as a service provider and a client of an English healthcare organisation (NHS England). It is concluded that it is critical to ensure a conceptual-based, proactive-care actions and services-experiences relationship mapped in root cause analysis through the provider's full awareness of initiation and decision making in order to create a positive AI-driven customer experience. These actions of the AI-driven financial services provider create a direct causal link to organisational building blocks of customer experience affecting the organisation's strategy, leadership buy-in, culture, organisational design and ready-systems of processes and technology.

Key words: *Accounting, Artificial Intelligence, Customer, Customer Experience Management, Financial Services, Machine Learning.*

Introduction

Leveraging new types of data in a digital era is rapidly becoming a necessity for financial service providers to stay competitive and reach underserved markets. Artificial Intelligence (AI) is perceived as a radical innovation that has the potential to disrupt the market and bring changes to the subsystems of the firm. An inclusive financial system is desirable and will fundamentally transform the financial services landscape through opportunities of access for all people, specifically, with the rise of banks and financial institutions. Customer-focused AI solutions are undergoing intensive exploration in the financial industry. This gives the finance industry an excellent opportunity to manage customer relationships through data management that reveals actual customer preferences rather than merely their intentions (Bonacchi, 2019). This transformative period shows that customer power tends to create a transition in the business model to shift to a more relationship-oriented or customer-centric view that appears as a necessary condition to sustain long-term business performance (Ramani, 2008). Business performances that involve client interactions carried out by AI interfaces include personalised financial planning and automated customer services which were deployed in the practice-led case study of PriceWaterhouseCooper (PwC) and the National Health Service. This is reflected in a comprehensive NHS financial analysis that ultimately succeeds in enabling technology disruption potential that has been carried out as one of PwC's fresh perspectives, and offers practical advice in the NHS's period of system transformation. AI becomes one of the long-term solutions to the challenges the NHS faces and consequently shows ways to build positive customer perspective in the financial industry nowadays.

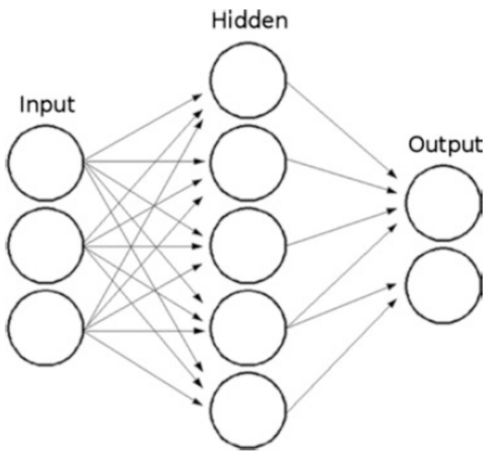
Literature Review
Artificial Intelligence

AI has become one of the faces featured in the digitalisation of the technology revolution. According to Verma (2018), AI is centred around the definition of the technological revolution premised on the ability of machines to replace human labour, perform repetitive tasks or perform tasks at a level well beyond the physical limits of humans. Several recent previous literature reviews have also concluded a similar basis for the definition of AI (Kaya, 2019; Wall, 2018; Hall & Pesenti, 2017; Tecucci, 2012). Tecucci (2012) stated that AI is an interpretation generated by training computers based on the simulation of human thinking patterns and behaviour. Wendy and Pesenti (2017) added that to reproduce such abilities in a computational system requires human intelligence, which includes learning and adaptation, understanding interaction sensory inputs, and reasoning in planning. A better autonomy and creativity complemented with the right procedures and parameters optimisation creates the ability to extract knowledge with predictions from extensive, diverse digital data. Wall (2018) considered that implementing AI starts in building a database of knowledge from human experts and applying this data in computer systems to better understand the complexity of simple problems. Kaya (2019) agreed that AI plays the role of computers demonstrating human-like cognitive skills that could result in immense efficiency gains or stronger profitability for firms and users. Contri & Galaski (2018) acknowledged AI as a moving target in this rapidly growing industry-dominant environment. They concluded a definition of AI as being a suite of technologies, enabled by adaptive predictive power and autonomous learning. AI could significantly advance user ability to recognise patterns, anticipate future events, generate ethical rules and decisions, and an improved communication system. As this was all built under the same deep roots, the study will discuss the developmental history of AI in the following section.

Types and Application of Artificial Intelligence (AI) in Financial Services

The development of AI has produced data-driven methodologies that facilitate the goals of performing a well-functioning financial institution. In this section, the paper will discuss three of the most applied AI techniques in the financial domain according to the studies of Bahrammirzaee (2010) and Gadre-Patwardhan et al. (2016), which are artificial neural networks (ANN), expert systems, and hybrid intelligence systems.

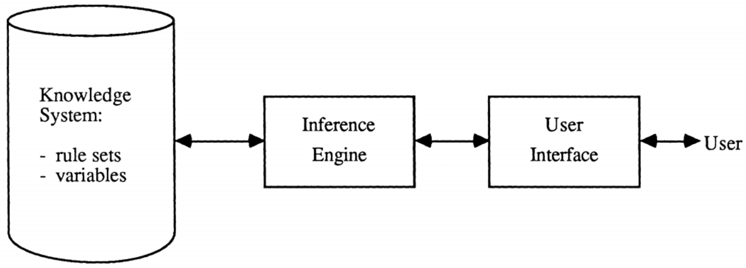
Figure 1. Three-layer architecture of ANN



Source: Gadre-Patwardhan et al. (2016)

Generally, **Artificial Neural Networks (ANN)** is a computational parallel processing system arranged in layers of neurons (input, hidden, and output layer) and interconnected by referred weights that emulate human pattern recognition function. Several ANN-based applications have been in wide-spread use for accounting and financial tasks. In this regard, various studies have focused on the review of ANN classifications. Taking a broad view, Hawley et al. (1990) claimed ANN to be best applied to problems that primarily attempt to solve for accuracy, classification, associative memory, and clustering. According to Bahrammirzaee's (2010) studies, ANN veritably performs better in issues that serve the aims above. For example, financial market information classification (Serrano-Cinca, 1997) which involves a better grouping process of bonds based on patterns in the issuers of financial data and agency ratings. Bankruptcy prediction using ANN has the lowest misclassification error rate that enhances the professional judgements of auditors in the presence of financial distress and going concern contingencies (Anandarajan et al., 2001).

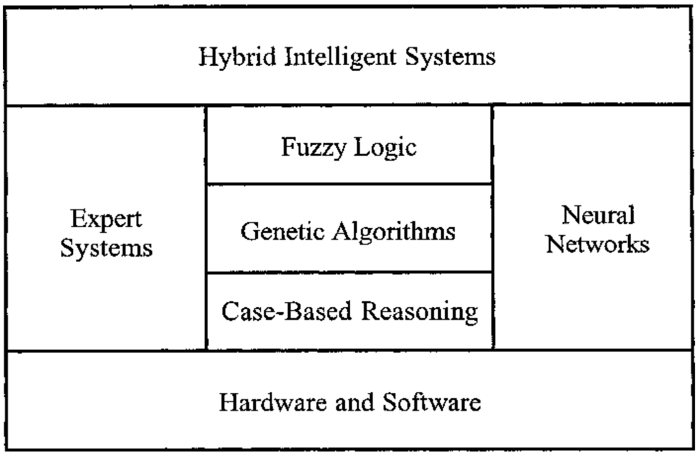
Figure 2. Generic Architecture of Conventional ES



Source: (Holsapple et al., 1988)

An expert system (ES) is a computer system of the well-organised body of knowledge that emulates expert problem-solving abilities in a limited domain. It requires a user interface to obtain information about the current decision environment, a knowledge base that contains the facts and heuristics of human expertise and a rule base to control the application of knowledge and interfaces (Hawley, 1990). ES's main features are to cope with situations of uncertainty or inexact reasoning and its correspondence in excelling decision rules of human expert emulation (Holsapple, 1988). Based on Bahrammirzaee's (2010) study, ES has a more promising performance in credit evaluation, fraud detection, financial prediction and investment planning to the extent that it was compared with conventional methods rather than ANN. This is likewise applied in an accounting study conducted by Changchit (2004), where ES was proven to strengthen the internal control system based on the evaluation of common sales and collection cycles where the auditors tend to play traditional roles.

Figure 3. Hybrid Intelligent System



Source: (Abraham et al., 2016)

Hybrid Intelligence Systems (HIS) is a robust learning system that combines the positive features to overcome the weakness of the processing capabilities and representations of learning paradigms, and it was proposed based on technique enhancement, the multiplicity of application tasks, and realising multi-functionality (Gadre-Patwardhan et al., 2016). In other words, HIS mixed methods and techniques of AI such as fuzzy expert system, neuro-fuzzy system, and genetic-fuzzy system. Primarily, a HIS that combines NN and fuzzy systems works well in enhancing judgmental systems for credit evaluation and credit risk management (Rast, 1997; Elmer et al., 1988; Dadios, 2012). Additionally, Romahi (2000) demonstrated successful financial forecasting in the stock market using traditional static ES approach fuzzy rule induction-based algorithms.

AI & Financial Services

Incorporating AI technologies into the business model enhances the insurance industry's value chain. AI increases the overall performance while enhancing customer experience and market base by altering the relationship, reinventing business platforms, and reducing social inflation that creates significant risk exposure to insurer liability (Kelly et al., 2018). The actuarial problems of the insurer, such as underwriting, claim processing, reserving and pricing in the face of a changing risk profile can be framed in AI context (Parodi, 2012). Broader access to more data points links AI-driven algorithms to the development of new plans and policies. As a result, the customer will be offered more customised policies and better-personalised planning based on budget, habits, and lifestyle (Larry, 2018). This section examines previous studies that are applicable to this research. It analyses the findings of Vasarhelyi & Kogan (1998) on their study toward the new paradigm of AI in the late 1990s. Vasarhelyi & Kogan (1998) compiled an extensive study consisting of many previous pieces of research that were analysing the past application of the expert system and the neural network in finance and accounting.

Table 1: Summary of previous research on customer-focused AI solutions

System Name	Authors	Research Area	Developing Methods
PLANMAN	McKell & Jenkins (1988); Brown (1990); Philips et al. (1992)	Financial planning (wealth growing management; insurance & risk management)	"C Language" Expert System
PLANPOWER	Stansfield and Greenfeld 1987; Connell, 1987; Brow 1988	Financial Planning Risk management, investment management	"LISP Language" Expert System
N/A	Hawley et al. (1990)	Credit approval & assessing lending	Artificial Neural System (ANS)

(Source: Vasarhelyi & Kogan (1998))

Table 2: Summary of previous research from individual review

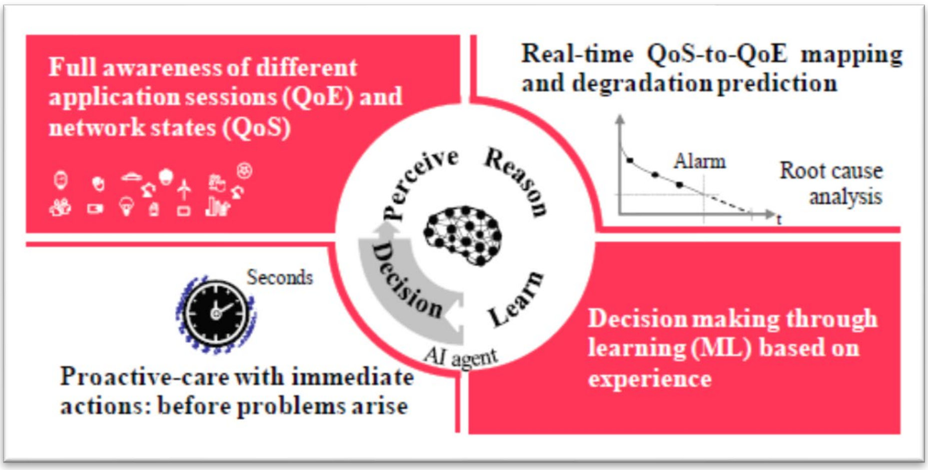
System Name	**Authors**	**Research Area**	**Developing Methods**
N/A	Martin & Eckerle (1991)	Health insurance claims	Expert system of knowledge and rule-based
Activation Model	Carey (1998)	Credit worthiness assessment	Neuristic hybrid model
N/A	Pau (1991)	Credit granting;	

		Customer financial planning	Forward chaining (rule-based ES); Backward chaining (knowledge-based) ES
N/A	Brockett et al. (1994)	Insurers property-liability risks	Artificial Neural Network (ANN)

Customer Perspective

Schmitt (2010) concluded a summarised definition that CEM incorporates the discipline, methodology, and transaction with a company, product, brand, or service comprehensively. CEM places some approaches to deliberately align the objectives and activities of the service provider with the assurance of an excellent customer experience delivery. Spiess et al. (2014) argue that for providers, measuring customer experience holistically is fundamentally a data analytics issue that can be effectively incorporated with a Customer Experience Management (CEM) analytics tool to help solve technical challenges and organisational barriers. Recently, Gacanin & Wagner (2019) discuss an AI-driven concept and vision of autonomous CEM that reduces the limitations of the quality independency of service (QoS) and experience (QoE) management in CEM by producing real insights about customer behaviour, notably through non-technical QoE indicators. Figure 2.6 illustrates a theoretical framework of AI-driven CEM conceptual function targeting problem root cause analysis and proactive-care actions in financial services.

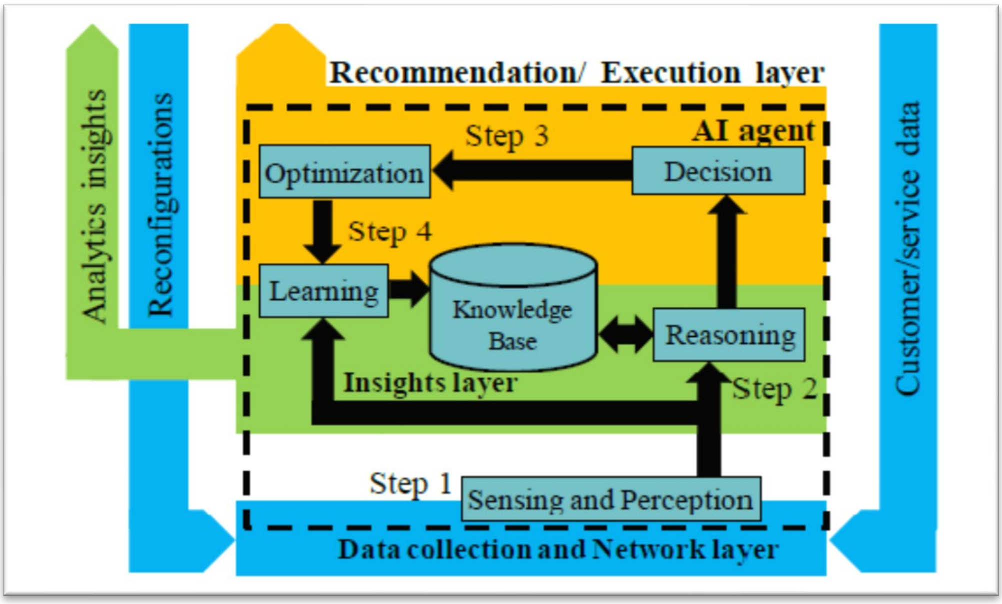
Figure 3. Conceptual Functions and enablers of autonomous (AI-driven) CEM targeting proactive-care and problem root cause analysis



Source: Gacanin & Wagner (2019)

Gacanin and Wagner (2019) added that data-driven analysis could be enabled through the learning of CEM frameworks layers and logical grouping of the AI functions observation (Figure 2.7) along with its characteristics determination (Table 2.3). The AI provider needs to be highly aware of the functions that are applied in the observable environments that have been adjusted to the desired utility or goals. This is achieved together with addressing a root cause analysis that firstly identifies the bottom line reason for a problem before ultimately reaching the recommended solutions. Marinaldi (2011) suggested in an internal audit term that this research-based approach requires a proactive commitment of time, resources, and effort to provide valuable problem validations that help strengthen the processing functions of the control environment by implementing the identified enhancement points.

Figure 4. Functional diagram of AI-driven CEM framework



Source: Gacanin & Wagner (2019))

The functions are elaborated in a way that sensing and perceiving steps helps establish data collection layer of behaviours that may include environmental level of measurements. This includes a continuous collection of network measurement, application parameters and data from other external systems which subsequently transform to data output. As detailed in Table 2.3, the data output then triggers other functions like reasoning function, which finds the best rational action in response to a problem state by defining the characteristics of the model belief state. The maximisation of expected utility in sequential decision problems is placed in the next function of decision making. The following optimisation function focuses on determining the planning device to achieve goals. Lastly, the state concludes with a learning function that produces knowledge based on the observed states which help improve reasoning enrichment function.

Benefit and Challenges

The increasing pace of AI applicability, in general, has generated a greater benefit to society. Through its capabilities, AI infuses efficiency into the provisioning of services and a cross-functional network. Kibria (2018) elaborates by stating that organisations can optimise the utilisation and maintenance flexibility to data-driven resources, which creates room for better planning and reductions in operating costs. This flexibility drives richer insights for analytics and improves user satisfaction in defining strategy execution. AI has the potential to identify the relationship of both hidden and new variables, which poses a better understanding of non-linear relationships (Wall, 2018). For example, this is essential for an organisation that employs new techniques in processing and facilitating autonomous customer care.

However, there is a causal relationship in an environment that involves a massive amount of data processing. Implementing data analytics through AI works closely with unique challenges. Common misconceptions are noted in a de Saint Laurent (2018) study where neutrality, objectivity, and the social values of AI are questioned. Practically, AI is not able to remove the existing biases of human prejudices, as AI requires relevant information that contradicts with neutrality and objectivity in deciding specific problems. The disruptive character of AI models creates uneasiness in marginalising societal impact in between the substitution of legacy to revolutionary technology (Holtel, 2016). Additionally, as relinquishing data is part of the prime process, automation creates the loss of direct control that is inevitable (Kibria, 2018). Increased data collection, which includes storing data online, could trigger cyber threats and privacy breaches (Rijcken, 2019). This links to ethical and legality issues as challenges that require meaningful human governance and scientific inquiry to assure a sustainable balance between artificial and human intelligence. In light of this, AI development should be encouraged through regulation and not restricted, particularly if such studies may hinder developments (Gurkaynak, 2016) and impose binding limits on individual behaviours (Wall, 2018). Cerka et al. (2015) discussed the existing legal doctrine for the potential damage of AI stated in article 12 of the Electronic Communications Convention (ECC) in 2011. It specifies that a person, whether a natural person or artificial (legal entity), on whose behalf a computer was programmed, should ultimately be responsible for any message generated by the machine. In other words, there is no legal personality ascribed to a stand-alone AI to say that it may not be held personally liable for the damages it causes. Strict liability will govern over the machine behaviour that is binding the natural person and legal entity on whose behalf it acted, with reference to developers of the AI system machines, users, and owners (Cerka et al., 2015). The same consensus was achieved in the RoboLaw project executed under the European Commission. The project reviewed and challenged the traditional fundamental legal personality categories to be aligned with creating a principle that protects the social safety over the full autonomous actions of machine characteristics. The project outcome concluded that AI might not be eligible for the compensation of damages (Cerka et al., 2017).

Methodology

A qualitative research approach has been chosen as a suitable way to fulfil the opportunity of theorising customer perspective of AI utilisations and formulating a comparative analysis of the expectations and insights of AI practice in the current trend. A two-tiered strategy was adopted for the literature review: 1) a general review on AI-related topics was carried out to establish the foundation of AI in terms of its use and value in technology domain 2) the second stage reviews the literature of AI application in financial services which is narrowed down to customer-focused uses. In selecting the journal for the second review, it was decided to search for literature from 1985 to 2000 to reflect the AI-past-paradigm period at a certain level of technological development. It was found the papers in the journals addressed various issues with respect to the design and type of AI used, adoption, and future research direction for AI as a developing topic.

After reading through the papers, a consensus to an organising framework was achieved. Customer perspective is measured under the conceptual function that is proposed by Gachanin & Wagner (2019), which ensures proactive care with immediate actions and real-time service-experience relationships mapping in root cause analysis through providers' initiation of full awareness and experience-based ML decision making. This framework will be applied to the collected case studies data of how the provider fulfils the AI-driven CEM framework's functions and its characteristics dependencies. These actions of AI-driven financial services providers will create a direct causal link through the study of Plessis & Vries (2016) on building blocks for the customer experience. It mentions five aspects affected in the organisations (strategy, leadership buy-in, culture, organisational design, ready-systems of processes and technology).

Analysis

Enabler of AI-Driven CEM Targeting Proactive Care in Financial Services

AI utilisations adopted in the organisational system have a significant influence on financial services, especially in building the right customer perspectives. In reflecting a positive customer perspective, it is imperative to ensure that positive service touch-points are made throughout the customer experience. Based on the literature review, a positive customer perspective is constructed from the first stage of reading the real-time quality of service and experience environment mapping, in the lens of root cause analysis along with the application of full awareness in identifying the gap that can be filled with AI solutions. Proactive care is the required next step that is applied to prevent worsened situations. These steps would eventually lead to decision making through AI. To choose the perfect AI solutions for organisational problems, running through the AI-driven CEM learning functions is essential to finally come to the acquired knowledge that is based on the observed states and increased ability to maximise the expected utility of the organisation.

Reflecting on the theoretical frameworks, PwC had identified the causal factors through its root cause analysis complemented with full awareness in observing the financial condition of the NHS. Proactive care action was carried out in the form of risk assurance and risk mitigation over the existing financial pressure experienced by the NHS. After bringing PwC's AI expertise insights into the personalised financial planning and autonomous customer service, PwC managed to offer AI solutions into NHS's decision-making process.

PwC indicates the potential shifts that attract more benefits to the system have dramatic implications. As the focus is to optimise a benevolent system and provide fulfilling healthcare outcomes, ensuring the system remains open and agile to technological disruption is the aspect that intersects with other aspects such as the public, patients, commissioning, finance, and workforce. Realising digital portals means making the flexible access to national data and the use of technology to promote uptake, implementation and behavioural change. This will raise questions regarding the NHS's affordability towards meeting its funding gap for the strategy. PwC, however, has looked over the risk assurance and mitigation of the NHS system that aligns with proactive care of immediate actions to prevent problems from arising. Gathering information on potential benefits, spending, and public perception leads to the conceptual function of decision-making through learning (Machine Learning) based on experience. Recently, this has been evidenced through PwC's service in giving their AI expertise in-depth understanding and ML that enables the automation of NHS's administrative practice. The breakthrough of AI and ML techniques through PwC is succeeding in more accurately predicting the length of stay for patients, creating more effective capacity planning and supporting more comprehensive strategic clinical designs.

CEM Framework and Logical Grouping of AI Functions Observation

It is unavoidable that AI has the potential for personalised financial planning in assisting medical advances, democratising expensive services, improving customer service and workforce capacity. The thorough assessments of associated utility and risk that PwC has carried out deliver a set of recommendations around interpretability, risk management, control, governance structure, and the platform assurance for the execution of a responsible AI (PwC, 2018). According to PwC's (2018), the AI adoption for NHS's problems falls under the ease of use of Recurrent Neural Network (RNN), Long Short-term Memory and Gated

Recurrent Unit Neural Network (LSTM & GRU), and Convolutional Neural Networks (CNN). This section will, therefore, analyse how these AI types used are assessed to be compatible with the functions of AI-driven CEM framework.

a. *Sensing and Perception*

Artificial Neural Network (ANN) has the nature of being a collection of artificial neurons that can be activated by the input data. A few data controllers in the NHS support the establishment of an open data ecosystem to gain insights processed in NHS Digital. NHS Digital transforms patient-based data for direct clinical care to design the Secondary Uses Service (SUS). It also contains detailed information about the admitted patient, outpatient, critical care in Hospital Episodes Statistics (HES) (Reform, 2018) that are useful for predicting patient length-of-stay as intended by PwC's ML solution. Below is detailed the established data collection layer for AI's NHS Digital following the framework in Table 1.

Table 3: NHS Data Collection Layer

Data Controller	Data Input	Data Processor
NHS Trust (Patient records, Diagnostic, Procedures)	- Commissioning Datasets - Diagnostic Imaging Datasets (DID) - Patient-Reported Outcome Measures (PROMs)	**NHS Digital**
Ambulances	- Emergency Care Datasets (ECDS)	**NHS Digital**
General Practitioners	- Clinical Practice Research Datalink (CPRD) - Summary Care Records - Quality & Outcome Frameworks	**NHS Digital**
Local Authorities	- National Child Measurement Programme - NHS Health Check Assessment	**NHS Digital**

Source: Adopted from Reform National Survey

b. *Reasoning*

PwC is aware of the technical transparent data requirement in making the AI algorithm for ML explainable. However, standard ML have no concern for causal reasoning to generate explainability ease beyond the statistical view (Reform, 2018) as PwC (2016) stated that the

RNN works around its predictive power when used with large amounts of sequenced information. Therefore, the *Probabilistic model* is the conditional dependence structure when faced with random variables in ML's statistics (AHSN, 2018).

c. *Decision-making*

PwC's AI utilisation is predominantly geared towards the potential economic utility of understanding the trends, patterns, and results of the management information across multiple predictions in ML (PwC, 2018). This makes PwC as *a decision-theoretic* agent that is guided in objectives of measuring critical components. This includes the economic utility (revenue), and the intelligence derived from the model, the accuracy of generalising the sensed data, the functional validation over given regulations for AI application, the impact on business reputation, and the potential harm of algorithm uses outcomes (PwC, 2018).

d. *Optimisation/Planning*

AI applications using ML devised in RNN, LSTM & GRU, and CNN will deliver a hypothetical concept that can refer to an AI that learns to perform different tasks within healthcare scenarios. These chosen model performances work to fulfil *constrained optimisation* of performance and return on investment by seeking to optimise cumulative rewards over time through choosing actions that result in 'high value' states (PwC, 2018).

e. Learning

RNN falls under the family of the ML method base, whose learning data representations can be *supervised*, *semi-supervised*, or *unsupervised* (AHSN, 2018). Supervised and unsupervised ANN can be used to generate models and extract trends concerning the targeted utility (Malek et al., 2012). When the desired output is adjusted to the observable data environment, these learning architectures are designed to extract the distilled knowledge for the AI system to acquire new insights (PwC, 2018).

Customer Touch-points through Personalised Financial Planning and Autonomous Customer Service

PwC has carried out the process of channelling a strategy into NHS's solution in the early stage of the case. This is exemplified by the PwC's action of understanding the NHS's service concepts through the reviewing of strategies discussed in the Impact Assessment by the Department of Health. It has enacted collaborative scenarios through further identification of additional actions that include benefits to be realised, potential scale evaluation, and system-based evidence drawings. After applying a service-to-experience congruence and addressing problems and service relevance, PwC suggested a strategy in the reinforcement of digital revolution and eventually AI adoption in the system, in which the NHS proceeded as relevant enactments of forming a visible design.

It is imperative to coordinate decision-making processes, budgets, and delivery vehicles to enable effective governance around appropriate discretionary and cross-functional commissioning. This requires strong, positive leadership for the development of team cohesiveness, the internal culture of flexibility and risk-taking to achieve a common understanding of the use of information and technology and prioritising the commitment of resources. PwC set up capabilities towards the prerequisites of delivering a transformational change of AI strategy through the authority establishment and approaches to design and technology. Business values should be demonstrated in the increased capability of redesign leadership commitment that articulates how it connects to a data-driven culture that blends behavioural change to support analytical insights, with a practical focus and actionable decisions across all levels (PwC, 2018).

As AI has been selected as the appropriate technology that aligns to corporate strategy and is perceived as a way to efficiency in eliminating obstacles in the customer chain, a high-level design is mapped and developed into an operating model. In the process of designing the interfaces, staff will interact with the AI system, which it is ensured will bring intuitiveness for staff and significant simplification in the current process. This is applied under the importance of human labour involved in system design and deployment of an AI system (Hardt, 2014). This, however, will result in the availability of personalised financial planning towards AI-enhanced services that will drive productivity gains from operation automation processes.

Conclusion

It was found that the AI interfaces used to solve administrative problems are fully compatible with Gachanin & Wagner (2019)'s AI-driven CEM framework. Additionally, PwC succeeded in building a positive customer perspective through the organisational building block elements it emphasised as the achieved desired outcome: a structural strategy incorporating the elements of leadership, culture, system design and technology. The inevitable radical change that AI brings to the industry opens spaces to maximise opportunities. As the success factor of AI has been identified with the ongoing advanced AI implementations in financial services, it has influenced the business model to change and eventually produce a significant effect via services delivered to customers. In this way, the maximisation of benefits will expand the financial industry to positive growth. However, the challenges of AI are not to be ignored; increases in customer trust and acceptance are still needed to unleash the full potential.

Limitations and Recommendations

This research is limited to the information provided in the public reports; thus, the interpretations should only be made with regard to the conceptual view of the performances indicated in these user case studies. However, as the area of AI application in financial services is still developing, it would be a good idea to be able to assess a practical AI-driven CEM in the financial field. A broader review of the former application of the AI era will drive more comprehensive insights that will possibly improve its reliability and accuracy.

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