Harnessing the future of machine learning

Applications of ML in risk management

October 2021

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Introduction

Machine learning (ML) techniques are creating waves within the financial services sector. The banking industry, which relies heavily on data, is increasingly adopting these techniques and has started to leverage their powerful capabilities.

From chatbots to fraud detection, the banking sector is using ML not only to automate processes and streamline operations for both the front and back offices, but also to enhance the overall customer experience. ML tools, with their advanced prediction techniques and capabilities to utilize large volumes of data, are increasingly being used in risk management. They may inform quicker and more efficient credit, investment and business-related decision making.

Another important area where ML is gaining significance, albeit at a slower pace, is regulatory stress testing. Traditional statistical methods of stress testing have been critiqued by investors and regulatory agencies as 'not severe enough', with numerous banks failing during crises.

In the following pages we discuss the application of ML in risk management, as well the benefits and challenges of adoption.

AI technologies

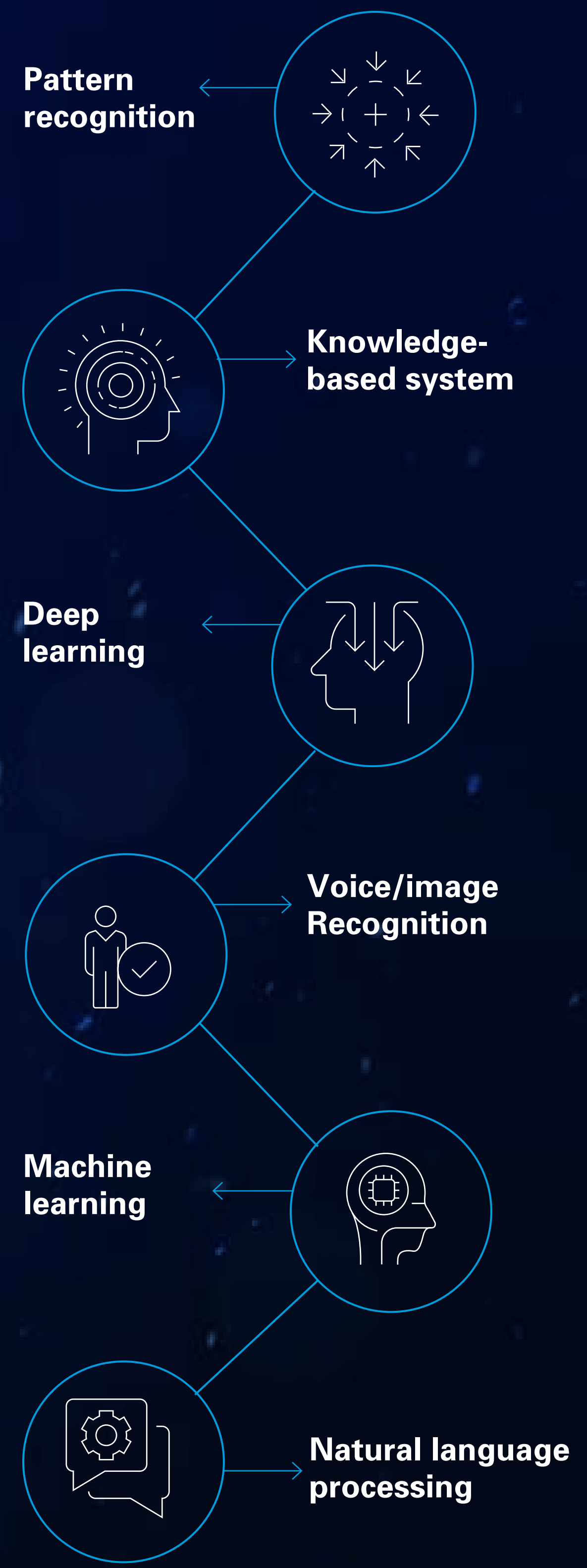
Risk assessment
Credit scoring, credit underwriting, stress testing

Portfolio management
Customer segmentation, recommendations

Trading
Algorithmic trading

Customer support
Chatbots, robo-advice

Fraud prevention
Anti money laundering (AML) and fraud detection



Applications

Machine learning is increasingly recognized for its potential to transform the day-to-day activities of a business. In risk management, ML has become synonymous with improving efficiency and productivity, while reducing costs. This is possible due to the technologies' ability to handle and analyze large volumes of unstructured data at fast speeds with considerably lower degrees of human intervention.The technology has also enabled banks and financial institutions to lower operational, regulatory, and compliance costs, while simultaneously providing banks with accurate credit decision making capabilities.

The emergence of non-traditional lenders, such as payment banks and technology-based non-banking financial companies, has resulted in an increasing number of firms using ML and technology-based algorithms in traditional banks. These entities have been forced to upgrade their legacy systems and architecture to assess credit profiles of customers.

They are also leveraging alternative data sources, such as social media photos and check-ins, GPS data, e-commerce, and online purchases, mobile data, and bill payments. The availability of Big Data has enabled banks to build robust AI-based internal models for decision making purposes.

ML solutions are thus able to provide the financial industry with trusted and timely data for building competence around customer intelligence, for successful implementation of their strategies and for restricting losses.

ML-powered risk management solutions can also be used for model risk management (back-testing and model validation) and stress testing, as required by global prudential regulators.

AI technologies

Credit risk

– Enabling of a more robust assessment of customer credit history
– Providing insight that reveals additional operational, financial, or economic vulnerabilities that traditional models could not provide
– Enhanced accuracy of internal credit scoring models

Market risk

- Reduction of risk in market trading
- Analyzing vast volumes of data points in seconds
- Providing traders with optimal price points
- Identification of trading patterns across multiple markets
- Enhanced accuracy of forecasting models

Fraud risk

- ML can quickly spot patterns from several different channels in tandem and send alerts about potentially fraudulent activity for a virtually limitless number of banking clients at once
- Successfully differentiate between legitimate and fraudulent transaction within milliseconds

Enterprise risk

- Enhanced decision-making through greater predictive insight and visibility of risks for senior management
- Enhanced risk monitoring mechanisms whereby ML can be used to predict the likelihood of default
- Identification of breaches in security and/or other business controls

Key benefits

Superior forecasting accuracy

Traditional models, such as linear regression, do not adequately capture non-linear relationships between the macro economy and a company's financials. This is particularly true in the event of a stress scenario. Machine learning offers improved forecasting accuracy, due to its ability to capture nonlinear effects between scenario variables and risk factors.

Optimized variable selection process

Feature/variable extraction processes take up a significant amount of time in risk models used for internal decision-making purposes. Machine learning algorithms, augmented with Big Data analytics platforms, can process huge volumes of data and extract many variables. A rich feature set with a wide coverage of risk factors can lead to robust, data-driven risk models for stress testing.

Richer data segmentation

Appropriate granularity and segmentation are critical when dealing with changing portfolio composition. Machine learning algorithms enable superior segmentation, taking many attributes into consideration. Using unsupervised machine learning algorithms, combining both distance and density-based approaches for clustering, results in higher modeling accuracy and explanatory power.

Improved scenario generation

Since decision-based models are forward looking, it is essential to forecast macro-economic variables under various scenarios. However, given the stress and volatility contained within these scenarios, accurate predictions are rare. This is where advanced ML techniques can enhance model accuracy, with respect to scenario generation, as a result of high computational power.

Use cases: staying ahead of the curve

1. Credit risk modelling

Banks frequently use traditional credit risk models to predict categorical, continuous, or binary outcome variables (default/non default). ML models are often difficult to interpret and may not be easy to verify for regulatory purposes. Nevertheless, they can still be used to optimize parameters and improve the variable selection process in existing regulatory models.

AI-based decision tree techniques can result in easily traceable and logical decision rules, despite having nonlinear characters. Unsupervised learning techniques can be used to explore the data for traditional credit risk modeling. Classification methods, such as support vector machines, can predict key credit risk characteristics, including probability of default (PD) or loss given default (LGD) for loans.

Financial services firms are increasingly hiring external consultants who use deep learning methods to develop their revenue forecasting models under stress scenarios

2. Fraud detection

Banks have used machine learning methodologies for credit card portfolios for years. Credit card transactions present banks with a rich source of data which may be used to process and train unsupervised learning algorithms. Historically, these algorithms have been highly accurate in predicting credit card fraud due to their ability to develop, train and validate huge volumes of data.

Credit card payment systems are embedded with workflow engines that monitor card transactions to assess the likelihood of fraud. The rich transaction history available for credit card portfolios presents banks with the ability to distinguish between specific features present in fraudulent and non-fraudulent transactions.

3. Trader behavior

Technologies such as natural language processing and text mining are increasingly used to monitor activity and identify rogue trading, insider trading and market manipulation.

By analyzing email traffic and calendar-related data, check in/check out times, and call times combined with trading portfolio data, systems are able to predict the probability of trader misconduct, potentially saving millions in reputational and market risk for financial institutions.

Associated risks and challenges

It is of no doubt that ML, if implemented properly, can transform the banking industry. Vast amounts of data and sophisticated techniques may be used to build models that enhance risk management. However, there is a downside. These models amplify many elements of model risk, which are often insufficient to deal with current mechanisms and frameworks.

For example, traditional models (such as logistic regression), which are often based on clear statistical theories, use linear and low dimensional data as inputs. ML models, such as neural networks, utilize features such as dynamic training, high-dimensional data, hyper parameters, complex non-linear relationships and linkages. Such features often render these models less transparent compared to traditional models. This, in turn, elevates model risk, as associated risks are harder to identify and assess.

As a result, many banks are proceeding cautiously, restricting the use of ML to low-risk applications. The following are the key risks and challenges associated with the usage of ML in risk management:

Interpretability

ML models have long been regarded as 'black boxes'. Associated methods are typically subject to a trade-off between explanatory power and predictive performance. A good predictive model can be very complex and thus may be hard to interpret. These models require niche expertise and manpower to develop, validate and monitor. However, banks may use robust model risk management policies to minimize inherent risks contained within the ML modeling framework.

Validation

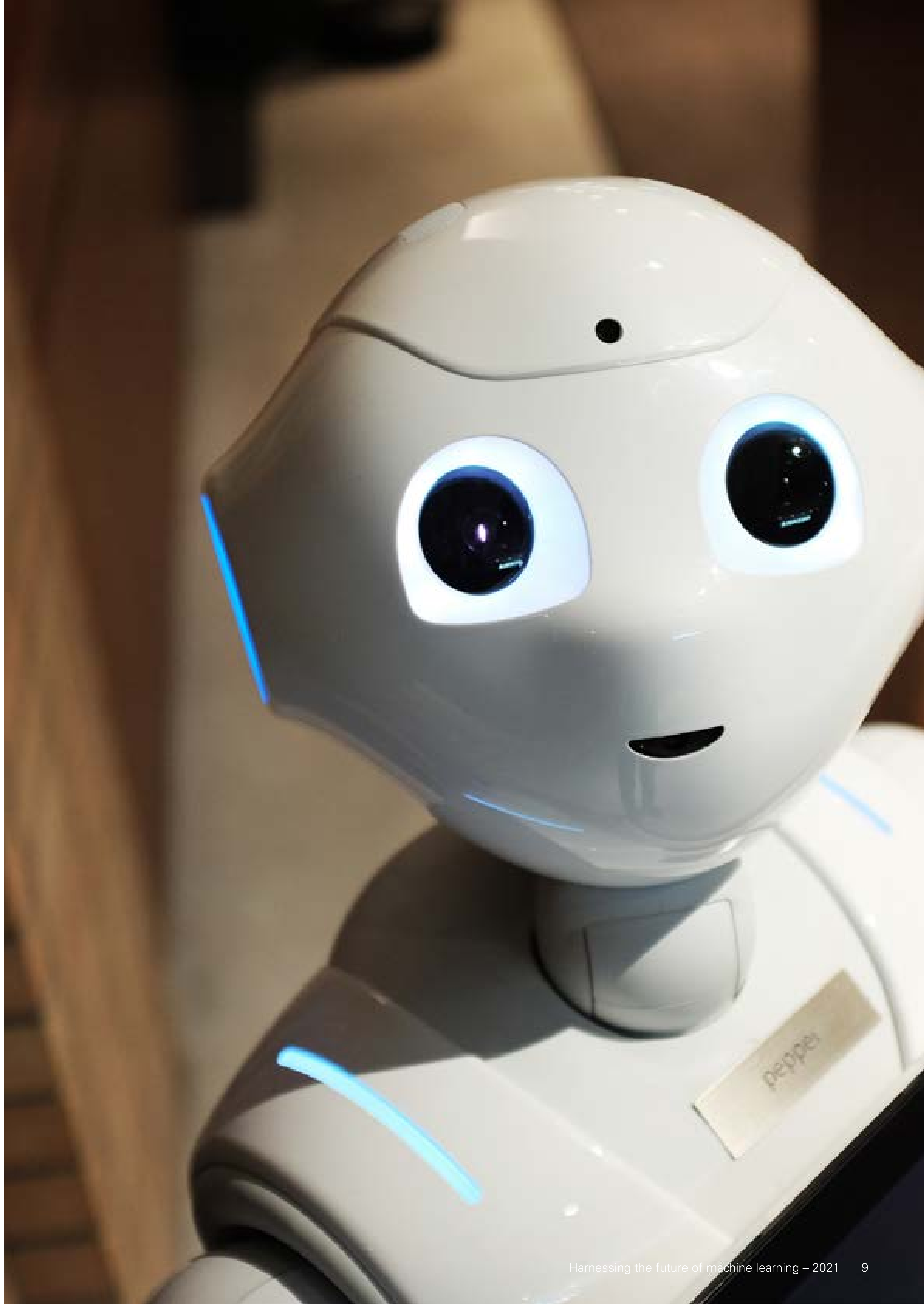
Given the unique features of ML algorithms and their 'black box' nature, thorough validation of these models (in areas such as conceptual soundness, process verification and outcome analysis, among others) poses significant challenges within existing validation frameworks, which are more suited to traditional regulatory models. In the context of internal models, validation techniques such as back testing become even more challenging since adverse scenarios usually do not actively materialize. Thus, in order to improve model quality, rigorous validation procedures customized to the needs of ML techniques should be in place.

Data integrity

High-quality data is of the utmost importance. ML models depend on high volumes of heterogeneous and high-dimensional data. Banks may need to enhance their existing data remediation processes and associated testing infrastructure. In addition, it may be necessary to document and trace lineage across the data life cycle.

Regulatory

There are no specific or stringent guidelines when it comes to the development and validation of ML models. Existing guidelines, such the Federal Reserve's SR11-7, provide guidance on model risk management, but may still need to be revisited and updated in the context of advanced ML modeling.



Future implications

The current global pandemic has taught us an important lesson – more than ever, banks need to be prepared to adequately handle a financial crisis.

Lessons from the past subprime crisis, coupled with a decade of post-crisis reforms, has already informed the banking industry's risk management mechanisms. Adopting artificial intelligence and machine learning techniques will likely lead to increased predictive power and replace outdated traditional statistical models. Such an evolution will require ever evolving model management.

Limitation of traditional models

The economic disruption caused by Covid-19 had severe implications for measuring, managing and mitigating risk exposures.

Traditional risk models were of limited use in forecasting defaults during the crisis. As a result, banks were unable to factor in rapid and evolving changes to the credit and economic environment. This was particularly true of industries that were severely impacted, such as airlines, hospitality, and leisure.

Higher predictive power

For most banks, existing models rely heavily on past events and historical data. ML can negate this. The deep learning aspect of the technology can provide enhanced predictive analysis based on real time data.

With increasing regulatory requirements and robust and agile setups backed by ML, leveraging innovative technologies will not only optimize the entire process but also enable quicker and more precise results.

Evolving model risk management

In the future, ML models may become more advanced, making them even more difficult to interpret, explain and manage.

As more complex models are rolled out and more decisions are made by autonomous models, risk management will evolve into a strategic risk, creating challenges that go beyond simple model risk management.

How KPMG can help

Artificial intelligence potentially offers faster decision making, enhanced accuracy, predictive power and more robust stress testing methods by automating human operations, leveraging the power of big data and reducing costs.

Embracing a rapidly advancing new technology that disrupts business as usual is not easy.

KPMG can help your organization seize the potential of artificial intelligence in the context of risk management. KPMG professionals are dedicated to working with you to create relevant, scalable solutions that drive value for your organization. We understand the issues and challenges involved in the development of a robust model risk management framework and KPMG professionals can leverage their experience to deliver tailored services.

Our suite of services provides full support at every stage of development - from proof of concept to designing relevant use cases, integrating systems and operations to ongoing management support. We can support your organization in leveraging the benefits of +ML technologies and incorporate these in risk management models. From scenario design, macro-economic modeling, and stress testing to IFRS 9 PD, LGD and exposure at default (EAD) models, incorporating both Pillar 1 and Pillar 2 risks, our teams are here to assist.

KPMG will keep you apprised of the growing artificial intelligence ecosystem, informed of new developments, and aware of the evolving regulatory landscape.

About KPMG

For almost 50 years, KPMG Lower Gulf Limited has been providing audit, tax and advisory services to a broad range of domestic and international, public and private sector clients across all major aspects of business and the economy in the United Arab Emirates and in the Sultanate of Oman. We work alongside our clients by building trust, mitigating risks and identifying business opportunities.

KPMG Lower Gulf is part of KPMG International Cooperative's global network of professional member firms. The KPMG network includes approximately 227,000 professionals in over 146 countries. KPMG in the UAE and Oman is well connected with its global member network and combines its local knowledge with international expertise, providing the sector and specialist skills required by our clients.

KPMG is widely represented in the Middle East: along with offices in the UAE and Oman, the firm operates in Saudi Arabia, Bahrain, Kuwait, Qatar, Egypt, Jordan, the Lebanon, Palestine and Iraq. Established in 1973, KPMG in the UAE and Oman employs 1,485 people across four offices, including about 100 partners and directors.

Our KPMG IMPACT initiative aims to help clients future-proof their businesses amid times of increasing focus towards issues such as climate change and social inequality. The goal is to help them achieve success across 17 major Sustainable Development Goals (SDGs) and become more resilient and socially conscious. For FY21, the firm has earmarked a global budget of USD 1.43 million for the initiative.

As we continue to grow, we aim to evolve and progress, striving for the highest levels of public trust in our work. Our values are:

Integrity: We do what is right.

Excellence: We never stop learning and improving.

Courage: We think and act boldly.

Together: We respect each other and draw strength from our differences.

For Better: We do what matters.

To meet the changing needs of our clients, we have adopted an approach aligned with our global purpose: Inspiring Confidence, Empowering Change. Our three pillars – exceptional quality of service, an unwavering commitment to the public interest, and building empowered teams – are the foundation of our firm.

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Designed by Creative UAE

Publication name: Harnessing the future of A.I.

Publication number:3675

Publication date: October 2021

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