

# **Information Technology in Organisations and Societies**

*This page intentionally left blank*

# **Information Technology in Organisations and Societies: Multidisciplinary Perspectives from AI to Technostress**

**EDITED BY**

**ZACH W. Y. LEE**

*Durham University, UK*

**TOMMY K. H. CHAN**

*Northumbria University, UK*

**AND**

**CHRISTY M. K. CHEUNG**

*Hong Kong Baptist University, Hong Kong*



United Kingdom – North America – Japan – India – Malaysia – China

Emerald Publishing Limited  
Howard House, Wagon Lane, Bingley BD16 1WA, UK

First edition 2021

Copyright © 2021 Emerald Publishing Limited

**Reprints and permissions service**

Contact: [permissions@emeraldinsight.com](mailto:permissions@emeraldinsight.com)

No part of this book may be reproduced, stored in a retrieval system, transmitted in any form or by any means electronic, mechanical, photocopying, recording or otherwise without either the prior written permission of the publisher or a licence permitting restricted copying issued in the UK by The Copyright Licensing Agency and in the USA by The Copyright Clearance Center. Any opinions expressed in the chapters are those of the authors. Whilst Emerald makes every effort to ensure the quality and accuracy of its content, Emerald makes no representation implied or otherwise, as to the chapters' suitability and application and disclaims any warranties, express or implied, to their use.

**British Library Cataloguing in Publication Data**

A catalogue record for this book is available from the British Library

ISBN: 978-1-83753-237-7 (Print)

ISBN: 978-1-83753-236-0 (Online)

ISBN: 978-1-83753-238-4 (Epub)



ISOQAR certified  
Management System,  
awarded to Emerald  
for adherence to  
Environmental  
standard  
ISO 14001:2004.

Certificate Number 1985  
ISO 14001



INVESTOR IN PEOPLE

# Dedication

To my parents, who have taught me to be kind.  
Zach W. Y. Lee

Tommy would like to dedicate this book to master Minho.  
Tommy K. H. Chan

For everyone, may you be blessed with good health and happiness.  
Christy M. K. Cheung

To all who have interest in learning about the impacts of information technology  
on our work and life.

*This page intentionally left blank*

# Contents

List of Figures and Tables	<i>ix</i>
About the Editors	<i>xi</i>
About the Contributors	<i>xiii</i>
Preface	<i>xvii</i>
Acknowledgements	<i>xxi</i>
<b>Chapter 1 AI and Its Implications for Organisations</b> <i>Madhav Sharma and David Biros</i>	<i>1</i>
<b>Chapter 2 Collaboration of Human and Machine for Knowledge Work: An Organisational Transformation Framework for Data-driven Decision-making</b> <i>Hanlie Smuts and Alet Smith</i>	<i>25</i>
<b>Chapter 3 Does Technostress Trigger Insider Threat? A Conceptual Model and Mitigation Solutions</b> <i>Forough Nasirpouri Shadbad and David Biros</i>	<i>61</i>
<b>Chapter 4 Sociological Mechanisms Behind ICT-Related Technostress in the Workplace</b> <i>Raluca Stana and Hanne Westh Nicolajsen</i>	<i>85</i>
<b>Chapter 5 An Integrative Framework of Cognitive Absorption for Technology Use</b> <i>Christy M. K. Cheung, Dimple R. Thadani and Zach W. Y. Lee</i>	<i>111</i>

<b>Chapter 6 Augmented Reality in Experiential Marketing: The Effects on Consumer Utilitarian and Hedonic Perceptions and Behavioural Responses</b> <i>Xuwei Yang</i>	147
<b>Chapter 7 Does Self-Disclosure on Social Networking Sites Enhance Well-Being? The Role of Social Anxiety, Online Disinhibition, and Psychological Stress</b> <i>Tommy K. H. Chan</i>	175
Index	205

# List of Figures and Tables

## Figures

Fig. 1.1.	AI Technologies.	6
Fig. 1.2.	Types of AI.	9
Fig. 1.3.	AI Systems Based on Agency of Technology.	12
Fig. 2.1.	Literature Search Outcome.	33
Fig. 2.2.	OTxDD Framework.	39
Fig. 2.3.	Final OTxDD Framework.	44
Fig. 2.4.	OTxDD Measurement Tool Extract (Actual Score Rating Illustrative).	44
Fig. 2.5.	The OTxDD Framework and Measurement Tool (Illustrative).	45
Fig. 3.1.	Technostress Creators.	65
Fig. 4.1.	Proposed Technostress Framework Listing ICT-related Technostressors and Technostrain.	89
Fig. 4.2.	Proposed Technostress Framework Listing ICT-related Technostressors and Technostrain.	107
Fig. 5.1.	Flowchart of Study Selection.	117
Fig. 5.2.	Current State of CA Research.	121
Fig. 5.3.	Integrative Framework of CA for Technology Use.	122
Fig. 6.1.	Research Model.	159

## Tables

Table 1.1.	Definitions of AI.	2
Table 1.2.	Definitions of AI Components.	4
Table 1.3.	Implications of Weak and Strong AI.	11
Table 1.4.	Implications of Hybrid Systems and Fully Autonomous Systems.	14
Table 2.1.	Enablers, Sub-Enablers and Framework Components Extracted from Papers Identified.	34
Table 2.2.	Components of the Proposed OTxDD Framework.	38
Table A2.1.	Dataset Created Based on SLR.	47
Table A2.2.	Challenges Highlighted During Data Analytics Assessment of the Organisation (Business Report).	51

*x List of Figures and Tables*

Table 3.1.	A Sample of Technostress Studies.	66
Table 3.2.	A Sample of Information Security in the Context of Technostress.	72
Table 4.1.	Obligations Surrounding the Application of ICT in the Workplace.	95
Table 5.1.	Summary of Theoretical Focus and Operational Definitions of Absorption, Flow and Cognitive Engagement.	114
Table 5.2.	The Dimensions of CA Adopted by Studies.	119
Table A5.1.	Summary of Studies on CA.	132
Table B5.1.	Summary of Psychometric Properties of CA and its Dimensions.	143
Table 6.1.	Measures.	160
Table 6.2.	A Summary of the Respondents' Profile.	162
Table 6.3.	AVE, Construct Reliability and Cronbach's $\alpha$ .	163
Table 6.4.	Item Loading.	164
Table 6.5.	Inter-Construct Correlation Matrix.	165
Table 6.6.	The Hypothesis Test Result.	166
Table 7.1.	Measurement Items.	185
Table 7.2.	Demographic Statistics of the Respondents ( $n = 234$ ).	188
Table 7.3.	Descriptive Statistics and Correlations.	190
Table 7.4.	Results of Hierarchical Regression Analysis.	191
Table 7.5.	Results of Moderated Regression Analysis.	192
Table 7.6.	Results of Moderated Regression Analysis.	193
Table 7.7.	Results of Hierarchical Regression Analysis.	194

## About the Editors

**Zach W. Y. Lee** is an Associate Professor at Durham University Business School and a Fellow of the Higher Education Academy. His research interests include organisational and societal implications of IT use, social media, online consumer behaviours, and digital service innovation. He has published in international journals such as *Industrial Marketing Management*, *Information Systems Journal*, *Information & Management*, *Journal of the Association for Information Science and Technology*, *Journal of Management Information Systems* and among others. Zach serves as an Associate Editor of *Internet Research* and is an editorial board member of *Industrial Management & Data Systems* and *Journal of Computer Information Systems*.

**Tommy K. H. Chan** is a Senior Lecturer at Northumbria University. Tommy's research interests include societal implications of information technology uses and online consumer behaviours. His work has been published in peer-reviewed journals such as *Journal of Management Information Systems*, *Information & Management*, *Information Systems Journal*, and *Industrial Marketing Management*. He serves as an Associate Editor at *Internet Research* and is on the editorial board at *Industrial Management & Data Systems* and *Journal of Computer Information Systems*. He has served as track co-chair, associate editor and programme committee of various tracks at international conferences on information systems.

**Christy M. K. Cheung** is a Professor and the Director of Research Postgraduate Programme of School of Business at Hong Kong Baptist University. She is the awardee of the RGC Senior Research Fellow scheme with the funding to advance research into the role of technology in the formation, prevention, and intervention of online collective deviant behaviour. She has published over one hundred refereed articles in international journals and conference proceedings, including *MIS Quarterly*, *Information Systems Research*, *Journal of Management Information Systems*, and *Journal of the Association for Information Systems*. Christy is currently the President of the Association for Information Systems (AIS-Hong Kong Chapter). She also serves as Editor-in-Chief of *Internet Research*.

*This page intentionally left blank*

## About the Contributors

**David Biros** is an Associate Professor of Management Science and Information Systems and Fleming Chair of Information Technology Management at Oklahoma State University. A retired Lieutenant Colonel of the United States Air Force, Dr Biros' last assignment was as Chief, Information Assurance Officer for the AF-CIO. His research interests included deception detection, insider threat, and information system trust. He has published in *MIS Quarterly*, *the Journal of Management Information Systems*, *Decision Support Systems*, *Group Decision and Negotiation*, *MISQ Executive*, *the Journal of Digital Forensics Security and Law* and other journals and conference proceedings.

**Hanne Westh Nicolajsen** holds a position as Associate Professor in the Department of Business IT at the IT University of Copenhagen, Denmark, and until 2020, was the Head of the Industrial Master's program in IT Management. Her research focusses on the management of implementation and adaptation of information systems as part of organisational change projects. Currently, she researches organisational innovation systems with a particular focus on the involvement of employees and technostress. Hanne has published her research so far in *Creativity and Innovation Management*, *Scandinavian Journal of Information Systems*, *Journal of Business and Industrial Marketing*, *Journal of E-Business Research*, *Library Management*, and *International Journal of E-services and Mobile Applications*.

**Forough Nasirpouri Shadbad** is a PhD Candidate in the Management Science and Information Systems department at Oklahoma State University. Her research focusses on intentional/unintentional insider threats, technostress, gamification, and information privacy in social networking sites. She has published in *Information Technology & People*, *Journal of Computer Information Systems*, and in the proceedings of the Americas Conference on Information Systems, the Hawaii International Conference on Systems Sciences, and other proceedings.

**Madhav Sharma** is a PhD Student, studying Management Science and Information Systems at Oklahoma State University. His research interests include Diffusion of Innovation, Use and Implication of Artificial Intelligence, Machine Learning, and Internet of Things. He has published in the *Cutter Business Technology Journal*, *Journal of Mid-west Association of Information Systems*, *Journal of Information Systems Education* along with many other conference proceedings.

**Alet Smith** is the General Manager of the data science capability at a South African telecommunications company and responsible for driving the organisation's data strategy. Alet started her career in information technology. Motivated by her passion for data, innovation and design science, she has successfully led and managed several key business intelligence-related initiatives in the Telecommunications industry. She is a visionary and energetic leader, who has grown and developed resources from graduate status into fully-fledged data subject matter experts. She demonstrates exemplary leadership through an effective engagement approach and her ability to unlock and drive value from the organisational data. Currently, Alet is a PhD candidate in the Information Systems department at the University of Pretoria. The title of her study is *A Big Data Value Framework for the Data-driven Organisation*.

**Hanlie Smuts** is an Associate Professor in the Department of Informatics in the Faculty of Engineering, Built Environment and Information Technology, University of Pretoria. Prior to joining the University, during her tenure in the industry, she was involved in the promotion of digital transformation, driving growth through personalised digital offerings and empowering customers through convenient and effective self-service. Her thorough understanding of the digital and adjacent ecosystems also enabled her to implement digital financial solutions for the mass markets in South, East, and West Africa. Her current research focuses on information systems and the organisation, with particular emphasis on digital transformation, disruptive technologies, and the management of big data and knowledge. The combination of these research areas enables cross-domain research in the field of knowledge visualisation as an organisational tool, as well as collaboration between human and machine knowledge for knowledge-related work. Hanlie is a National Research Foundation rated researcher and has published several papers and book chapters in her field of study.

**Raluca Stana** is a PhD Fellow at the IT University of Copenhagen, Denmark, in the Department of Business IT. Her research focusses on leadership, technostress, and obligation. Raluca teaches classes on leadership and technostress and collaborates closely with practitioners. She has a practitioner's background, working with leadership, Big Data, and IT systems implementation in a large corporation, where she has experienced technostress personally and in her team.

**Dimple R. Thadani** is currently an Assistant Professor in Information Systems at Nottingham University Business School (NUBS) China. Prior to joining UNNC, Dimple was a Lecturer (School of Business) and an Administrative Staff (Teaching and Learning Centre) at Hong Kong Baptist University. Dimple received her PhD from City University of Hong Kong in 2013. Her research interests include social media, leadership and online collaborative games, e-commerce, and e-learning. She has published in international journals and leading information systems conference proceedings. Dimple received the best PhD Student Award at the 4th World Summit on the Knowledge Society.

**Xuewei Yang** is a Postgraduate Student at Durham University. She also holds a BA (Hons) degree with First Class in International Business from Coventry University. Her research interests include online consumer behaviours, social marketing, and evolutionary consumer psychology.

*This page intentionally left blank*

# Preface

Information technology (IT) use is typically regarded as a positive phenomenon that generates desirable outcomes. However, the negative consequences of IT use have been increasingly witnessed in recent years. For instance, individual users may experience 'technostress' from personal social media use and IT use in the workplace, and organisations may experience losses in productivity and assets due to employees' failure to comply with information security policies. Thus, researchers have called for further investigation into the negative and positive effects of IT use.

This book, *Information Technology in Organisations and Societies: Multidisciplinary Perspectives from AI to Technostress*, contains multidisciplinary research on the positive and negative aspects of IT use at both the individual and organisational levels, and covers emerging phenomena and topics ranging from artificial intelligence (AI), augmented reality, and organisational transformation to technostress. The book endeavours to provide contrasting views on the positive aspects and outcomes of digitisation and on the potential harms induced or exacerbated by advanced IT. The book also presents innovative discussions on strengthening the benefits of IT use and mitigating its drawbacks.

The studies in this book examine the implications of IT along a continuum from the organisations to the individual. The book starts with chapters on examining the implications of IT specific to the organisational context, and includes studies on the implications of AI for organisations, the organisational transformation framework for data-driven decision-making, and the relationships between technostress and employees' non-compliance with information security policies. Later chapters address the implications of IT in relation to organisations as well as individual users and consumers, with studies that develop an integrative framework for cognitive absorption, examine technostress in the workplace through sociological mechanisms, and explore the impacts of augmented reality on experiential marketing. The final chapters examine the impacts of IT specifically at the individual level, including an examination of the relationship between self-disclosure on social networking sites (SNSs) and well-being, and a literature review on social media stress. The diversity of the studies is also manifested geographically, with contributors from institutions and organisations across Africa, Asia, Europe, and America; methodologically, by using case study, design science, interview, literature review, and survey approaches; and theoretically, with theories ranging from organisational transformation frameworks, sociological

mechanisms, the person–artifact–task model, the stimulus–organism–response model, and the hyperpersonal communication model, to the transactional model of stress arising from the use of SNSs.

The book represents a collective effort not only to consolidate studies on emerging issues and phenomena related to the positive and negative aspects of IT use but also to prescribe future research avenues in connected research domains. The book adds to the growing body of knowledge on the multifaceted nature and outcomes of IT use. It is particularly relevant and appealing to academics and researchers working on IT use research, and should serve them well as a handy reference to the field.

The first chapter of the book, by Madhav Sharma and David Biros, presents an overview of the implications of AI for organisations through a discussion of the core components of AI, the organisational goals that could be achieved with AI, the various types of AI, and their interrelationships. The authors also cover the unintended consequences and vulnerabilities of using AI systems in an organisational setting. The chapter offers a balanced discussion of the benefits and drawbacks of AI systems, and concludes with recommendations for organisations on the development and implementation of AI.

The second chapter, by Hanlie Smuts and Alet Smith, presents an organisational transformation framework for data-driven decision-making (OTxDD) based on a collaboration between humans and machines. The authors use the design science research approach to develop the OTxDD framework, which consists of four major enablers (data analytics, data management, data platform, and data-driven organisation ethos) and twelve sub-enablers, together with an organisational measurement tool. Organisations can use the OTxDD framework and the measurement tool to create a transformation path to data-driven decision-making, applying insights from both knowledge workers and intelligent machines.

While the adoption and diffusion of advanced IT can enhance individual and organisational performance, there are some negative aspects, such as technostress and information security threats. In the third chapter, Forough Nasirpour Shadbad and David Biros propose a conceptual model to explain the relationships between technostress and employees' non-compliance with information security policies, suggesting that a higher level of perceived technostress is associated with a higher likelihood of employees violating such policies. Measures to reduce technostress and mitigate organisational security threats are discussed.

The fourth chapter, by Raluca Stana and Hanne Westh Nicolajsen, examines IT-related technostress in the workplace using sociological mechanisms. Having identified a lack of investigation of the social environment in which technostress arises, the authors examine technostress in the workplace through the sociological lens of obligation. They use an embedded case study in Denmark to examine political materials and interview employees from multiple organisations. The findings suggest that technostress may be socially constructed, and the authors suggest that a future research direction could be to view technostress as a societal responsibility.

With the growing interest in the uses of hedonic technologies and the gamification of system design, the concept of cognitive absorption, a holistic experience arising from technology use, has become increasingly important in explaining IT usage behaviours at both the organisational and the individual levels. The fifth chapter, by Christy M. K. Cheung, Dimple R. Thadani, and Zach W. Y. Lee, proposes an integrative framework of cognitive absorption in technology use that summarises the antecedents and consequences of cognitive absorption. The framework offers a foundation for future theory building and provides system developers with practical insights into the design of next-generation hedonic and immersive technologies.

The sixth chapter, by Xuewei Yang, continues with an examination of a particular emerging immersive technology, augmented reality, in the context of experiential marketing. Drawing on the stimulus–organism–response model, the author proposes and tests a research model that explains the effects of augmented reality media characteristics on consumers’ value perceptions, and how these influence their purchase intentions. The findings show that augmented reality media characteristics positively influence consumers’ utilitarian and hedonic value perceptions. The study provides marketers with insights into implementing digital transformation strategies and augmented reality applications in marketing practices.

The proliferation of SNSs has changed how we communicate, network, and socialise with others. The seventh chapter, by Tommy K. H. Chan, explores how social anxiety influences self-disclosure on SNSs and its effect on well-being. Drawing on the hyperpersonal communication model, the author advances a research model to explain how social anxiety leads to self-disclosure on SNSs. The author also hypothesises that online disinhibition has a positive moderating effect on the relationship between social anxiety and self-disclosure. This study enhances our understanding of the self-disclosure patterns of socially anxious individuals on SNSs, providing practitioners and educators with insights into how intimate relationships and a higher level of social interaction with others can be fostered.

Research on the positive and negative implications of IT across organisations and individuals has gained momentum, and the broad reach of this edited book contributes to the movement. We hope that both researchers and practitioners will enjoy reading the book and will derive new insights that inform their future research and practice. We thank the contributors and the publisher for making this book possible.

*This page intentionally left blank*

# Acknowledgements

We are grateful to the contributors of this book, David Biros, Forough Nasirpour Shadbad, Hanne Westh Nicolajsen, Madhav Sharma, Alet Smith, Hanlie Smuts, Raluca Stana, Dimple R. Thadani, and Xuewei Yang, for committing to the work and for engaging with the editors in a friendly, professional, and collegial manner. We would also like to thank colleagues from the institutes of the editors, who have provided constructive feedback to the development of this book and its initial proposal.

Lastly, we would like to express our gratitude to Emerald Publishing and their editorial team for producing and publishing this book. This book would not have been possible without their support.

Zach W. Y. Lee  
Tommy K. H. Chan  
Christy M. K. Cheung

*This page intentionally left blank*

## Chapter 1

# AI and Its Implications for Organisations

*Madhav Sharma and David Biros*

### Abstract

The nature of technologies that are recognised as Artificial Intelligence (AI) has continually changed over time to be something more advanced than other technologies. Despite the fluidity of understanding of AI, the most common theme that has stuck with AI is ‘human-like decision making’. Advancements in processing power, coupled with big data technologies, gave rise to highly accurate prediction algorithms. Analytical techniques which use multi-layered neural networks such as machine learning and deep learning have emerged as the drivers of these AI-based applications. Due to easy access and growing information workforce, these algorithms are extensively used in a plethora of industries ranging from healthcare, transportation, finance, legal systems, to even military. AI-tools have the potential to transform industries and societies through automation. Conversely, the undesirable or negative consequences of AI-tools have harmed their respective organisations in social, financial and legal spheres. As the use of these algorithms propagates in the industry, the AI-based decisions have the potential to affect large portions of the population, sometimes involving vulnerable groups in society. This chapter presents an overview of AI’s use in organisations by discussing the following: first, it discusses the core components of AI. Second, the chapter discusses common goals organisations can achieve with AI. Third, it examines different types of AI. Fourth, it discusses unintended consequences that may take place in organisations due to the use of AI. Fifth, it discusses vulnerabilities that may arise from AI systems. Lastly, this chapter offers some recommendations for industries to consider regarding the development and implementation of AI systems.

*Keywords:* Artificial intelligence; analytics-based prediction; machine learning; deep learning; computer vision; natural language processing

## Introduction

For over 100 years, the Artificial Intelligence (AI) umbrella has extended to include the most advanced technologies of each time period. Research in AI has been scattered across disciplines with a few common threads of understanding (Stone et al., 2016). According to Oxford Reference, which aggregated definitions from AI across 11 notable sources across disciplines, AI is defined as ‘the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages’ (Oxford, 2020). The largest contributor to research in AI has been computer science which has investigated technical advancement and validity of these systems. Recently, with widespread adoption, applied sciences such as information systems also have shown interest in this area with respect to business analytics and cybersecurity. Table 1.1 lists other definitions of AI appearing across disciplines of computer science and business.

Table 1.1. Definitions of AI.

Discipline	Authors	Definition
Computer Science	Nilsson (2014)	‘Artificial intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment’
	Simon (1995)	‘A branch of computer science that studies the properties of intelligence by synthesizing intelligence’
	Oxford (2020)	‘The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages’
Management Information Systems	Rai et al. (2019)	‘Machines performing the cognitive functions typically associated with humans, including perceiving, reasoning, learning, interacting, etc.’
Marketing	Shankar (2018)	‘Programs, algorithms, systems, and machines that demonstrate intelligence’
	Syam and Sharma (2018)	‘Involves machines mimicking intelligent human behavior’

Despite the fluidity of understanding of AI, the most common theme that has stuck with AI is ‘human-like decision making’ (Simon, 1995). Advancements in processing power of graphical processing units (GPUs), big data technologies-enabled highly accurate prediction algorithms and robotics have brought AI closer to human-like decision making and actions. Many machines can now perform (and sometimes even outperform) the cognitive functions typically associated with humans, including perceiving, reasoning, learning and interacting (Rai, 2020).

The current state of AI involves highly accurate predictive algorithms and automation of processes to some degree (Sharma & Biros, 2020). This makes AI cover a multitude of technologies across industries. Some prevalent trends include medical recommendation algorithms, consumer recommendation algorithms, dynamic pricing in travel sites, automatic targeted ad-engines, resume-parsing and hiring algorithms, just-walk out automated storefronts, translators, and self-driving vehicles, which are examples of some pervasive AI systems (Brynjolfsson, Hui, & Liu, 2019; Brynjolfsson & Mitchell, 2017; Brynjolfsson, Rock, & Syverson, 2018). With a notable projected market value of \$3.9 trillion by 2022 (Columbus, 2019) and a growing knowledge workforce (Miller & Hughes, 2017), these applications are approaching the status of general-purpose technologies which have the potential to significantly alter the economic and social structure of the society (Brynjolfsson et al., 2018). This is evidenced by tech-giants such as Google, Facebook and Apple which leveraged AI systems to gain prominence (Rayport, Kelley, & Schwalb, 2018). Yet, there have been instances of AI failures that have caused financial, social and legal harm to parties associated with the implementation of AI (Biros et al., 2019). Additionally, AI systems’ potential to partially or fully replace human workforce directly affects organisational structures and processes (Brynjolfsson et al., 2018).

This chapter provides a deeper understanding of AI and related technologies and their use in organisations. First, we discuss the components of AI and how they interact with each other. Second, we explore common goals and objectives organisations can fulfil with AI systems. Then, we examine the different types of AI systems and their implications on organisations. Fourth, we discuss potential vulnerabilities of AI systems and possible unintended consequences. The chapter ends with some recommendations for organisations that use AI currently or intend to adopt it in the future.

## **Components of AI**

For organisational contexts, AI systems are technological tools that generate value by increasing the scale of efficiency or use by introducing automatic prediction-based decisions and autonomous responses. Currently, AI encompasses technologies that combine analytics and automation, such as machine learning (ML), deep learning, natural language processing (NLP) and computer vision (Stone et al., 2016). Table 1.2 details the definitions of each of these technologies. Two common components in all AI systems are analytics-based prediction and automation. Both of them have varying degrees of interaction in AI systems.

Table 1.2. Definitions of AI Components.

<b>Technology</b>	<b>Description</b>
Machine Learning	‘Machine learning is the study of computer algorithms that allow computer programs to automatically improve through experience’ (Mitchell, 1997)
Deep Learning	‘A class of machine learning techniques that exploit many layers of non-linear information processing for supervised or unsupervised feature extraction and transformation, and for pattern analysis and classification’ (Deng & Yu, 2014)
Reinforcement learning	‘A framework that shifts the focus of machine learning from pattern recognition to experience-driven sequential decision-making’ (Stone et al., 2016)
AutoML	‘Machine learning where data cleaning, feature engineering, algorithm selection, hyperparameter tuning, as well as most other steps are done automatically’ (Larsen, 2018)
Internet of Things (IoT)	‘Connectivity of physical objects equipped with sensors and actuators to the internet via data communication technologies’ (Oberländer, Röglinger, Rosemann, & Kees, 2018)
Robotics	‘Concerned with how to train a robot to interact with the world around it in generalizable and predictable ways, how to facilitate manipulation of objects in interactive environments, and how to interact with people’ (Stone et al., 2016)
Computer vision	‘Computer Vision has a dual goal. From the biological science point of view, computer vision aims to come up with computational models of the human visual system. From the engineering point of view, computer vision aims to build autonomous systems which could perform some of the tasks which the human visual system can perform (and even surpass it in many cases)’ (Huang, 1996)
NLP	‘Computers understand, interpret and manipulate human language’ (SAS, 2020)

### ***Analytics-based Prediction***

Evolving from decision support systems (DSSs) in the 1980s, business intelligence in the 1990s, business analytics in 2000s to big data in 2010s, data-driven decision making has been a fundamental part of organisations (Sharda, Delen, & Turban, 2016). Analytics-based systems (DSSs, expert systems) have added value to organisations over time by informing their users about data-driven insights and improving their decision making.

The analytics-based prediction component of AI is led by ML which involves the use of algorithms that learn to make decisions directly from data rather than having their decisions programmed by a human. Recently, the most notable of these is neural networks (Mitchell, 1997). There are three paradigms in ML: supervised, unsupervised and reinforcement learning. Supervised learning is the learning function that maps inputs to outputs according to labelled training data (examples of input–output pairs) (Russell & Norvig, 2010). Unsupervised learning is a learning function that detects patterns in data with no pre-existing labelled data (Locatello et al., 2019). In reinforcement learning, a machine or a software agent interacts with its environment (by producing decisions) and learns by trial and error (Kaelbling, Littman, & Moore, 1996).

Deep learning is a subset of ML that exploits the use of dense multi-layered neural networks for pattern analysis (Deng & Yu, 2014). Where ML almost always requires structured data, deep learning uses multiple layers of neural network to extract higher-level features from raw unstructured data. Together, a combination of these technologies generates models based on existing data which inform future decision making.

### ***Automation***

The decisions are then converted to cognitive actions using robotics and the Internet of Things (IoT) components. Robotics automate the processes using cognitive elements. IoT uses sensors and actuators to both collect data from environments and produce actions. Together these technologies automate many repetitive, data-intensive tasks. The most pervasive of which is human language understanding using NLP and automated labelling of images and videos using computer vision. NLP is used in a wide array of automatic response systems or chatbots and conversational systems. Notable examples include Apple’s Siri, Amazon’s Alexa, and Google assistant systems. Computer vision is widely used in medical diagnosis, autonomous vehicles, and automated storefronts like Amazon Go. ML and deep learning enable machines to learn how to make predictions based on the data they are provided, leading to capabilities like being able to interpret natural language and identify objects in images. The machines can then be programmed to make informed decisions resulting in AI technologies such as chatbots, AI assistants, and automated storefronts. IoT and robotics components provide AI technologies with avenues of data collection and physical agency to conduct their functions. For example, autonomous cars couple computer vision (based on trained ML algorithms) and robotics. Fig. 1.1 shows the relationship between different technologies and their interactions, forming AI systems.

### **Goals**

To develop and implement AI systems, an organisation needs three resources: reliable data, technology and data science labour. The advent of personal apps, ubiquitous IoT and social media has increased typical organisations’ data collection capabilities to a great extent. With open-source algorithms and affordable

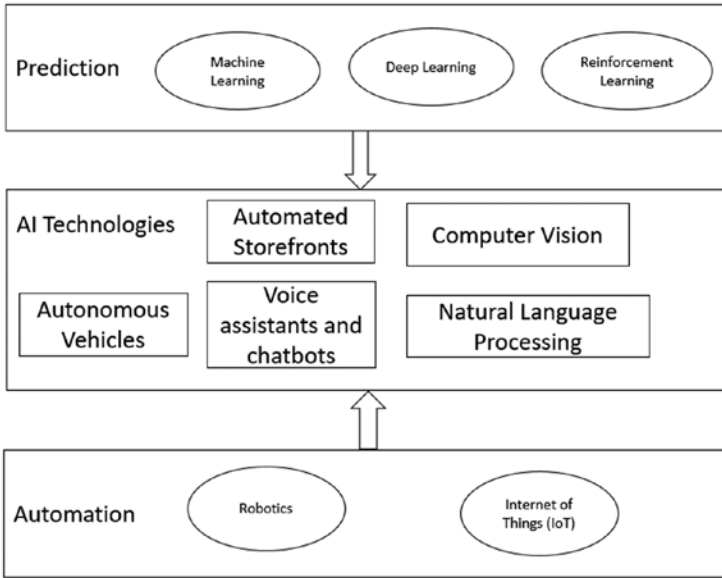


Fig. 1.1. AI Technologies.

access to high-performance GPUs, the technology to develop and implement an AI system is within reach of organisations across all tiers and sizes (Brynjolfsson et al., 2018). The data science labour force has grown substantially in the past decade to meet the high demand. With all three resources in reach, all tiers of organisations (small, medium and big) can develop and implement AI systems to add value to their enterprise. AI can add value to organisations by meeting one or more of the following objectives.

***Standardisation***

Some organisations use AI systems to develop and implement technical standards and set criteria to eliminate variance arising from human judgement. Typically, these are weak AI systems or hybrid systems with AI as an expert. They enable the organisations to make dispassionate data-driven decisions which make their decision-making processes more uniform. This may promote fairness and make it easier for the organisation to choose without favouritism. Another example of standardisation, NASA’s use of AI system to evaluate potential planets. AI algorithm trained on NASA’s Kepler telescope was able to identify 50 new exoplanets (planets outside our solar system) from historical NASA data (Yeung, 2020). Examples of this goal for AI include evaluations of teachers in schooling systems and credit card approval apps (Wilson & Daugherty, 2018). Using AI to evaluate teachers across a school district or state, or evaluating credit card applications of customers across the country ensures that all entities are rated based on the same variables without any individual bias.

### ***Personalisation***

Personalisation of products and services by predicting consumer behaviour was a prominent theme in organisation's use of IT in its initial years (Fan & Poole, 2006). Transaction processing systems with loyalty programs gave organisations access to data that can predict purchase habits of users. Scholars investigated consumers' willingness to trade their privacy for customised products that suited their needs (Awad & Krishnan, 2006). As IT became ubiquitous decades later, use of browser cookies, search histories and social media data enables organisations to have more data points to track consumer behaviour. This access to data points about consumers increased exponentially with the widespread adoption of IoT such as smart speakers, virtual assistants, and wearable devices. Consumer-driven organisations push to appeal to their clientele by tailoring their products and services towards specific individuals using available data (Wilson & Daugherty, 2018). With AI systems' ability to process large amounts of data quickly and generate recommendations, it can add value to these consumer-driven companies. Examples of use of AI in personalising products and services can be seen across industries ranging from retail, fitness, social media and entertainment. Notable illustrations include success of personalised fitness equipment and programs from Peloton, Apple, Mirror and others (Koetsier, 2020). Amazon's product recommendation algorithm processes data about the consumer from various sources such as shopping history, browsing history, and inquiries from conversational assistant to send targeted advertisements to individuals. Similarly, Netflix's algorithm is trained for specific users and recommends movies they may like.

### ***Reducing Human Involvement***

AI can be used by organisations to reduce human efforts in repetitive tasks. Fully or partially autonomous systems eliminate or reduce the need for humans to do tasks that can be easily automated increasing efficiency and adding value to the organisations. With a reduction in human effort, human error can also be reduced or taken out of the equation as exemplified by the use of autonomous vehicles. In the case of fully autonomous systems used internally by the organisation, AI systems replace human employees for certain tasks that AI can perform. Unlike humans, AI systems do not need to take breaks or change shifts leading to AI systems' use in storefronts and related places remarkably increase efficiency (Brynjolfsson et al., 2018). For example, a 30-year veteran driver who tested a self-driving truck said that the AI system could scan the road for a longer distance and react over 15 times faster than human drivers (CBS, 2020).

### ***Maximising Use***

Machine and deep learning-based predictive analytics is capable of processing large amounts of input data in a short time. The automation elements of AI make these systems capable of generating considerable amounts of output as well. Combining these attributes, AI systems can resolve many operational bottlenecks which can lead to increased use of their products and services by their users in

terms of frequency and time of use. This goal can be coupled with personalisation and reducing human involvement to make systems which increase the frequency and time of a product or service's use for consumers (Makridakis, 2017; Wilson & Daugherty, 2018). Use of AI systems to fulfil this objective has led to vital changes in organisational structure. Industry leaders such as Apple, Microsoft and Google, where once were known for their (hardware and software) landmark products are now venturing into more service-oriented structures (Gurman, 2019). Examples of AI systems being used in industry include AI-enabled virtual assistants used for customer care that can handle a higher volume of customers than human customer care associates at a lower cost. Heavy use of recommendation algorithms by social media sites such as YouTube and Facebook to increase engagement on their platforms is also an example of use of AI by organisations for this goal (Kumar, Rajan, Venkatesan, & Lecinski, 2019).

### ***Signal Innovation***

AI systems encompass buzz words and trending technologies. Organisations' emphasis on new technologies has proven to have positive reactions from the stock market and media (Hayes, Hunton, & Reck, 2001; Steelman, Havakhor, Sabherwal, & Sabherwal, 2019). Top management of some organisations opt for the use of AI systems in order to appear more innovative than their peers and gain legitimacy as per the institutional theory (DiMaggio & Powell, 1983; Jensen, Kjærgaard, & Svejvig, 2009). Evidence of these objectives can be seen in both big and small organisations. Success stories of AI systems creating value for organisations may also motivate organisations to develop and implement AI systems that do not fit their direct business needs. For example, IBM developed strong AI (Watson) without a pre-set market segment (Strickland, 2019). AI systems like these may not yield profits but are successful in positively reflecting organisations' research and development capabilities. Use of AI to signal innovation is more prominent in small to medium-sized enterprises. Many start-ups market themselves based on their AI prowess to attract investors. It was found that 40% of European start-ups that use AI in their description did not have any AI-related product or service (Vincent, 2019). In pursuit of one or a more of these goals, organisations may choose to design and implement AI systems. There are different types of AI systems that fit different problems organisations may aim to address. In the following section, we discuss different types of AI.

## **Types of AI**

We have discussed components of AI systems and goals that can be achieved with their aid. We have talked about AI in general terms, but AI systems are of different types (as shown in Fig. 1.2). They can be classified based on task orientation and agency. Task orientation refers to the range of tasks an AI can perform (Searle, 1980). Agency of technology refers to the degree of control of AI system has in performing its functions (Sundar, 2020). These classifications