智慧金融量化分析
(Artificial Intelligence in Finance and Quantitative Analysis)

AI 金融科技: 金融服務創新應用
(AI in FinTech: Financial Services Innovation and Application)

1101AIFQA02
MBA, IM, NTPU (M6132) (Fall 2021)
Tue 2, 3, 4 (9:10-12:00) (8F40)

戴敏育 副教授
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國立臺北大學 資訊管理研究所
Institute of Information Management, National Taipei University
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2021-10-05

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
1	2021/09/28	智慧金融量化分析概論 (Introduction to Artificial Intelligence in Finance and Quantitative Analysis)
2	2021/10/05	AI 金融科技: 金融服務創新應用 (AI in FinTech: Financial Services Innovation and Application)
3	2021/10/12	投資心理學與行為財務學 (Investing Psychology and Behavioral Finance)
4	2021/10/19	財務金融事件研究法 (Event Studies in Finance)
5	2021/10/26	智慧金融量化分析個案研究 I (Case Study on AI in Finance and Quantitative Analysis I)
6	2021/11/02	財務金融理論 (Finance Theory)

課程大綱 (Syllabus)

國立臺北大學
National Taipei University

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7	2021/11/09	數據驅動財務金融 (Data-Driven Finance)
8	2021/11/16	期中報告 (Midterm Project Report)
9	2021/11/23	金融計量經濟學 (Financial Econometrics)
10	2021/11/30	人工智慧優先金融 (AI-First Finance)
11	2021/12/07	智慧金融量化分析產業實務 (Industry Practices of AI in Finance and Quantitative Analysis)
12	2021/12/14	智慧金融量化分析個案研究 II (Case Study on AI in Finance and Quantitative Analysis II)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
13	2021/12/21	財務金融深度學習(Deep Learning in Finance); 財務金融強化學習 (Reinforcement Learning in Finance)
14	2021/12/28	演算法交易 (Algorithmic Trading); 風險管理 (Risk Management); 交易機器人與基於事件的回測 (Trading Bot and Event-Based Backtesting)
15	2022/01/04	期末報告 I (Final Project Report I)
16	2022/01/11	期末報告 II (Final Project Report II)
17	2022/01/18	學生自主學習 (Self-learning)
18	2022/01/25	學生自主學習 (Self-learning)

AI in FinTech:
Financial Services Innovation and Application

FinTech ABCD

AI

Block Chain

Cloud Computing

Big Data

Decentralized Finance (DeFi)

Block Chain Financial Technology

Block Chain & Bitcoin (BTC)

Smart Contract & Ethereum (ETH)

Decentralized Application (DApp)

FinTech

Financial Technology
FinTech

“providing
financial services
by making use of
software and
modern technology”

Source: https://www.fintechweekly.com/fintech-definition

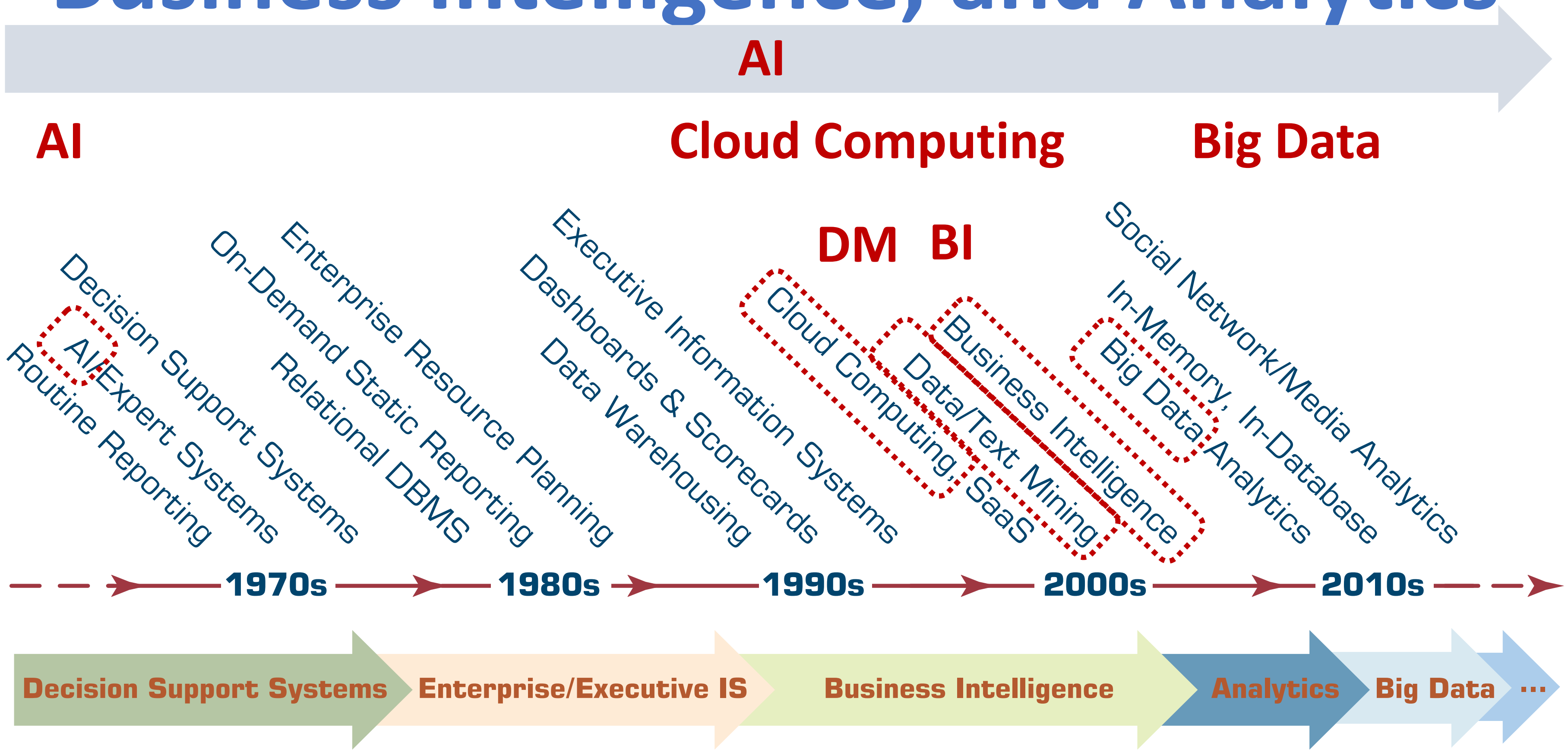
Financial Services

Financial Services

Source: http://www.crackitt.com/7-reasons-why-your-fintech-startup-needs-visual-marketing/

AI, Big Data, Cloud Computing

Evolution of Decision Support, Business Intelligence, and Analytics



AI

AI

Cloud Computing

Big Data

DM BI

Routine Reporting

AI/Expert Systems

Decision Support Systems

Relational DBMS

On-Demand Static Reporting

Enterprise Resource Planning

Data Warehousing

Dashboards & Scorecards

Executive Information Systems

Cloud Computing, SaaS

Data/Text Mining

Business Intelligence

Big Data Analytics

In-Memory, In-Database

Social Network/Media Analytics

1970s 1980s 1990s 2000s 2010s

Decision Support Systems

Enterprise/Executive IS

Business Intelligence

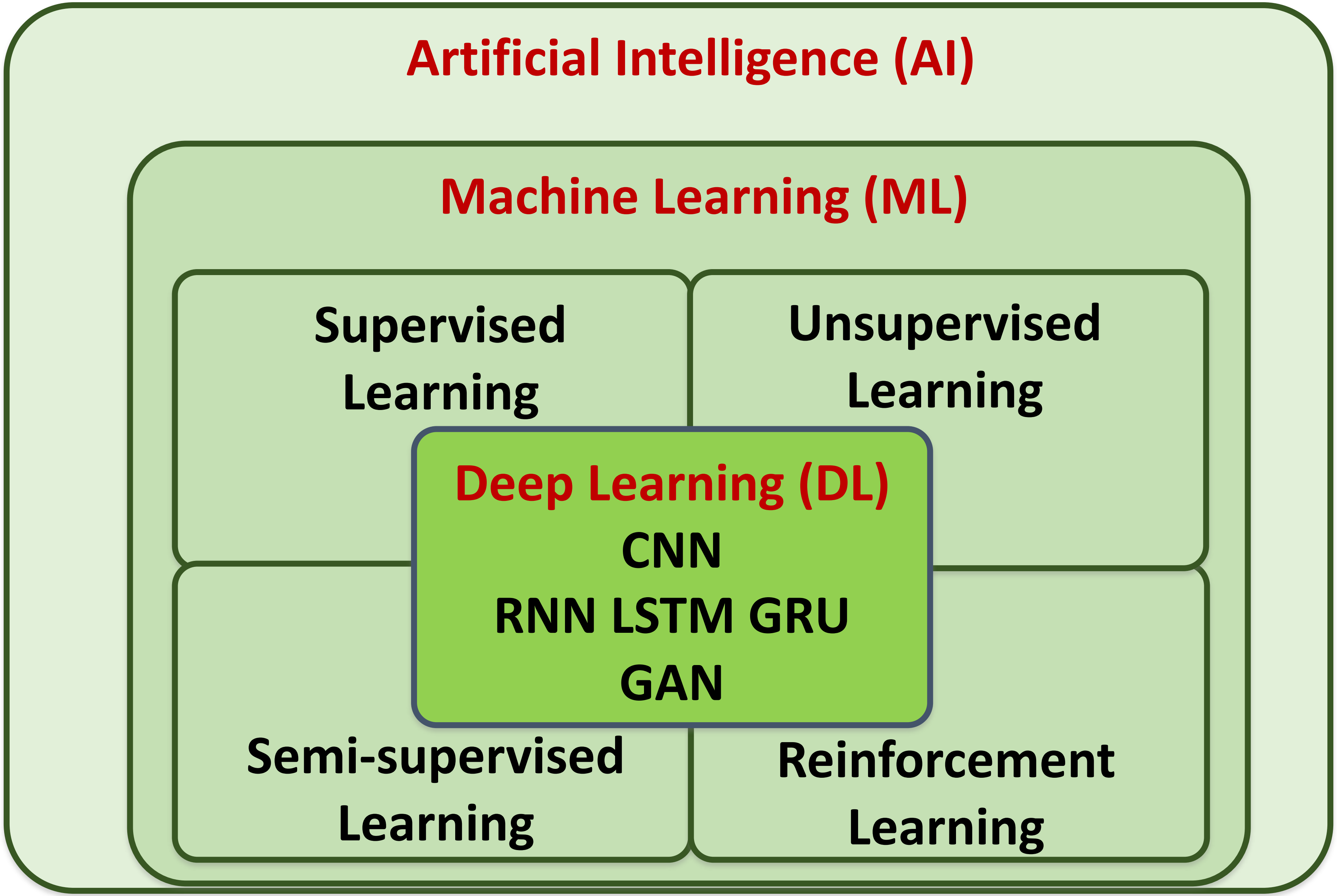
Analytics

Big Data

...

Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017),
Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

AI, ML, DL



Artificial Intelligence (AI)

Machine Learning (ML)

Supervised Learning

Unsupervised Learning

Deep Learning (DL)

CNN

RNN LSTM GRU

GAN

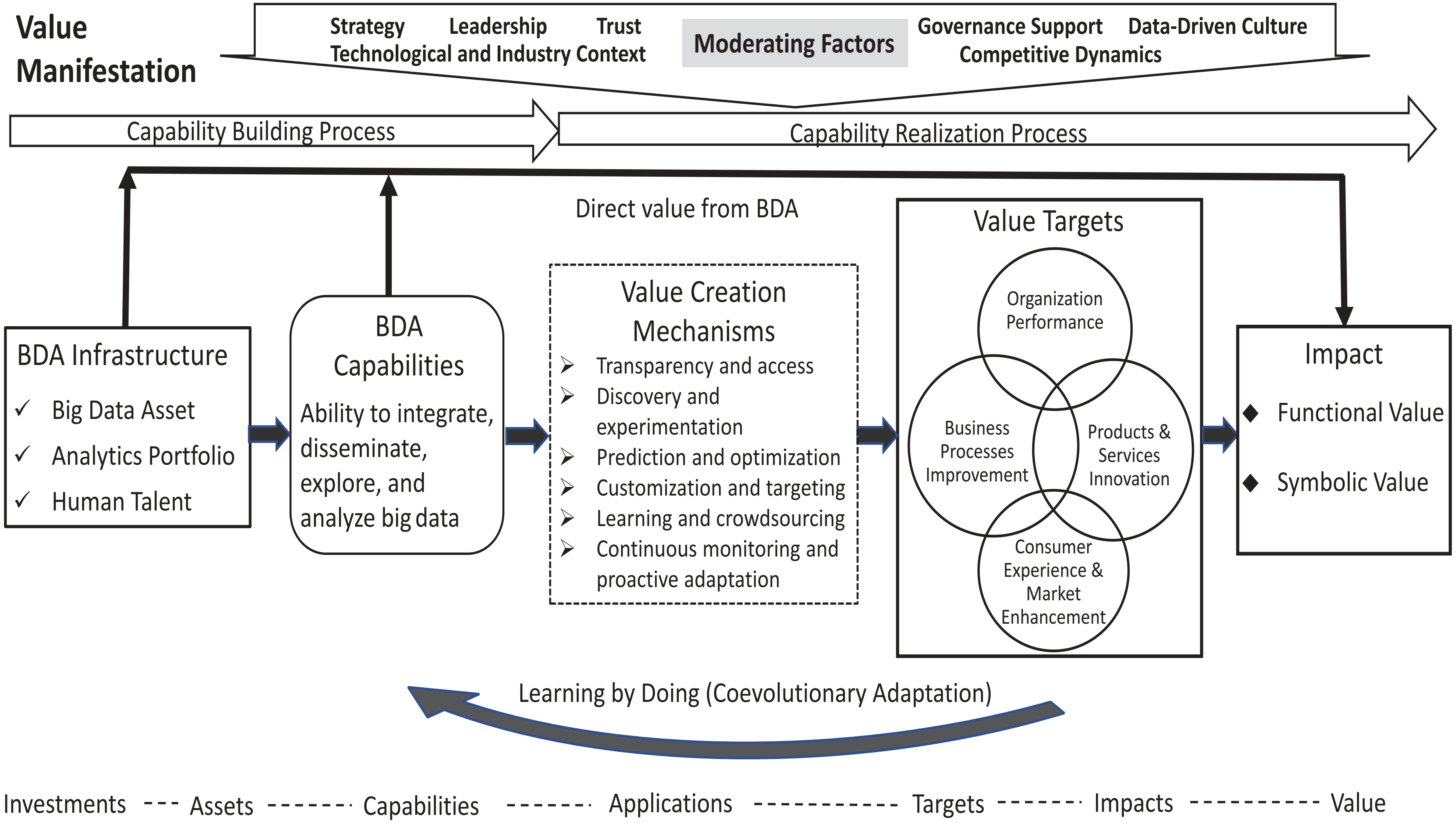
Semi-supervised Learning

Reinforcement Learning

Source: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/deep_learning.html

Value Creation by Big Data Analytics

(Grover et al., 2018)



Value Manifestation

Strategy
Leadership
Trust
Technological and Industry Context

Moderating Factors

Governance Support
Data-Driven Culture
Competitive Dynamics

Capability Building Process

Capability Realization Process

Direct value from BDA

BDA Infrastructure
- ✓ Big Data Asset
- ✓ Analytics Portfolio
- ✓ Human Talent

BDA Capabilities

Ability to integrate, disseminate, explore, and analyze big data

Value Creation Mechanisms
- ➢ Transparency and access
- ➢ Discovery and experimentation
- ➢ Prediction and optimization
- ➢ Customization and targeting
- ➢ Learning and crowdsourcing
- ➢ Continuous monitoring and proactive adaptation

Value Targets

Organization Performance

Business Processes Improvement

Products & Services Innovation

Consumer Experience & Market Enhancement

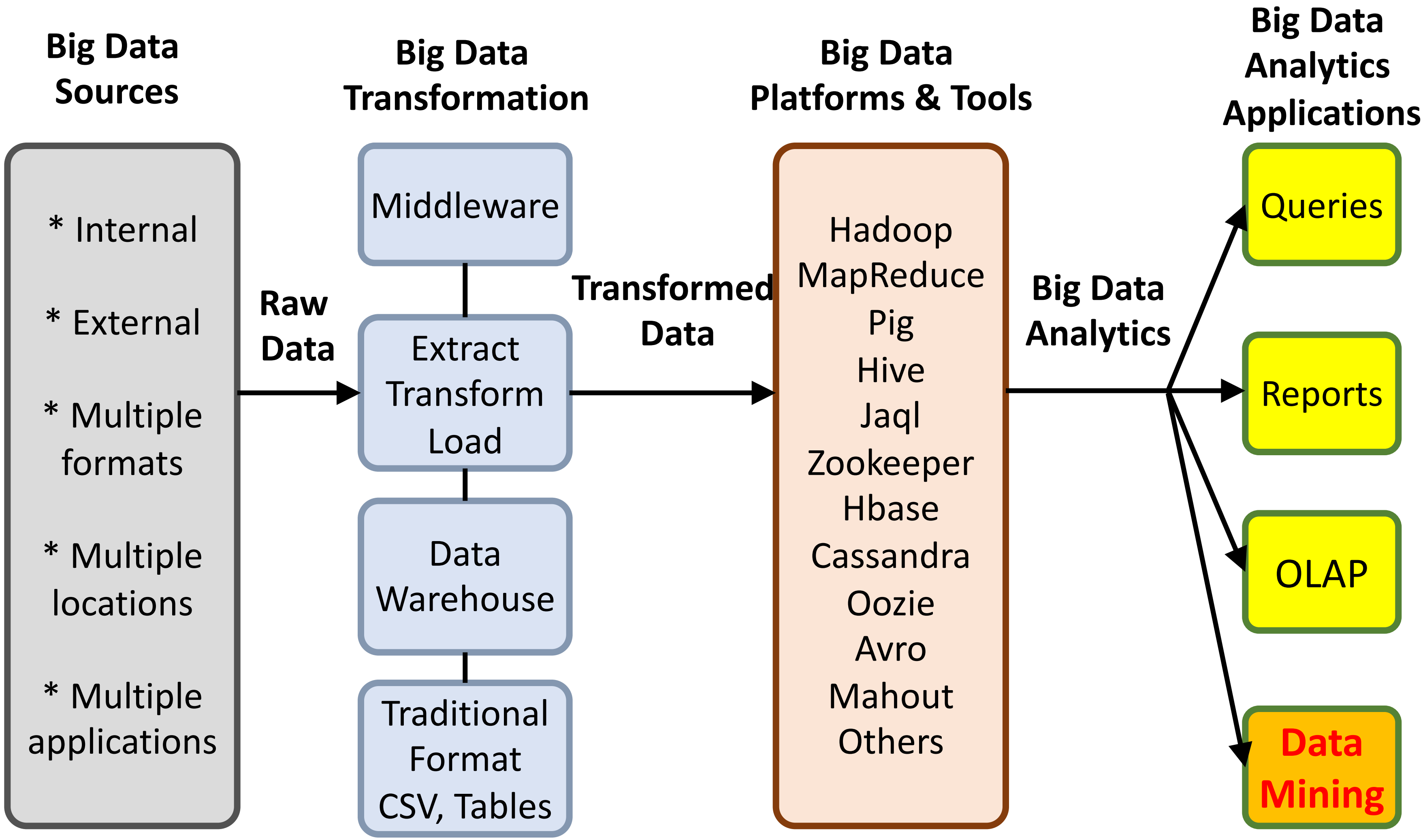
Impact
- ◆ Functional Value
- ◆ Symbolic Value

Learning by Doing (Coevolutionary Adaptation)

Investments --- Assets ------ Capabilities ------ Applications ----------- Targets ------ Impacts ---------- Value

Source: Varun Grover, Roger HL Chiang, Ting-Peng Liang, and Dongsong Zhang (2018), "Creating Strategic Business Value from Big Data Analytics: A Research Framework", Journal of Management Information Systems, 35, no. 2, pp. 388-423.

Architecture of Big Data Analytics



Big Data Sources

* Internal
* External
* Multiple formats
* Multiple locations
* Multiple applications

Raw Data

Big Data Transformation

Middleware

Extract Transform Load

Data Warehouse

Traditional Format CSV, Tables

Transformed Data

Big Data Platforms & Tools

Hadoop
MapReduce
Pig
Hive
Jaql
Zookeeper
Hbase
Cassandra
Oozie
Avro
Mahout
Others

Big Data Analytics

Big Data Analytics Applications

Queries

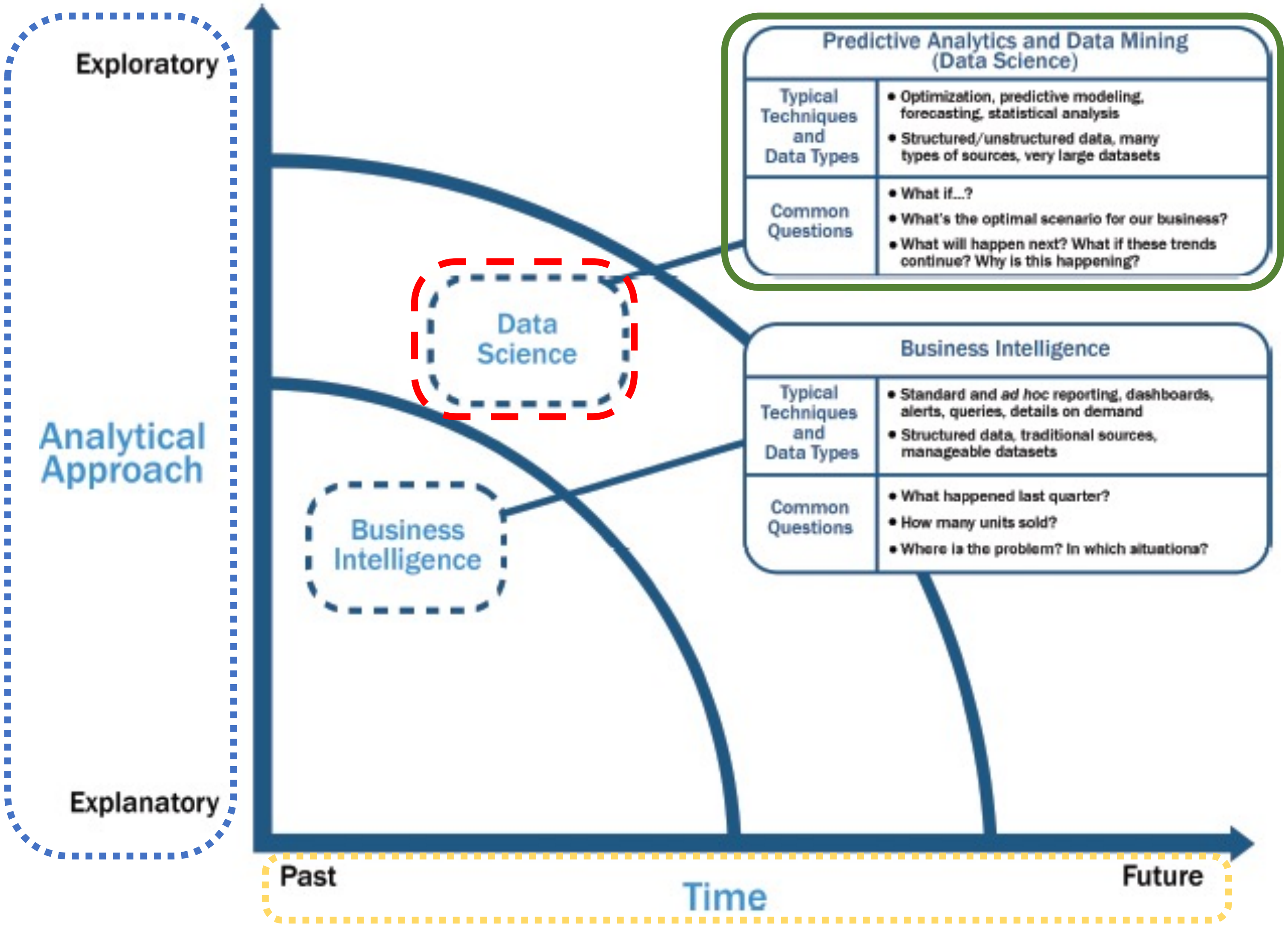
Reports

OLAP

Data Mining

Source: Stephan Kudyba (2014), Big Data, Mining, and Analytics: Components of Strategic Decision Making, Auerbach Publications

Data Science and Business Intelligence

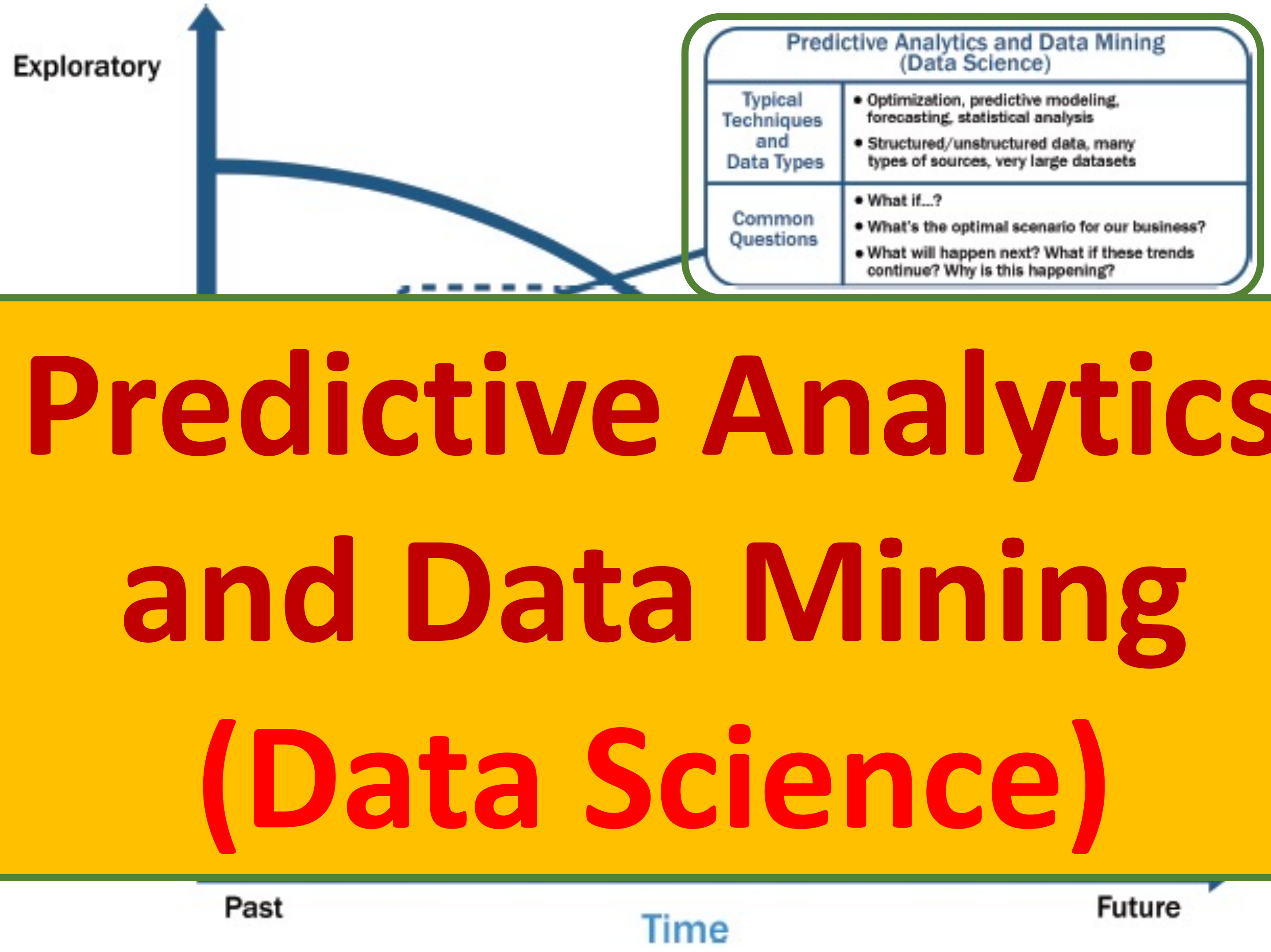


Predictive Analytics and Data Mining (Data Science)	
Typical Techniques and Data Types	• Optimization, predictive modeling, forecasting, statistical analysis • Structured/unstructured data, many types of sources, very large datasets
Common Questions	• What if...? • What's the optimal scenario for our business? • What will happen next? What if these trends continue? Why is this happening?

Business Intelligence	
Typical Techniques and Data Types	• Standard and *ad hoc* reporting, dashboards, alerts, queries, details on demand • Structured data, traditional sources, manageable datasets
Common Questions	• What happened last quarter? • How many units sold? • Where is the problem? In which situations?

Source: EMC Education Services, Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data, Wiley, 2015

Data Science and Business Intelligence



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Predictive Analytics and Data Mining (Data Science)

Source: EMC Education Services, Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data, Wiley, 2015

Predictive Analytics and Data Mining (Data Science)

Structured/unstructured data, many types of sources, very large datasets

Optimization, predictive modeling, forecasting statistical analysis

What if…?
What's the optimal scenario for our business?
What will happen next?
What if these trends countinue?
Why is this happening?

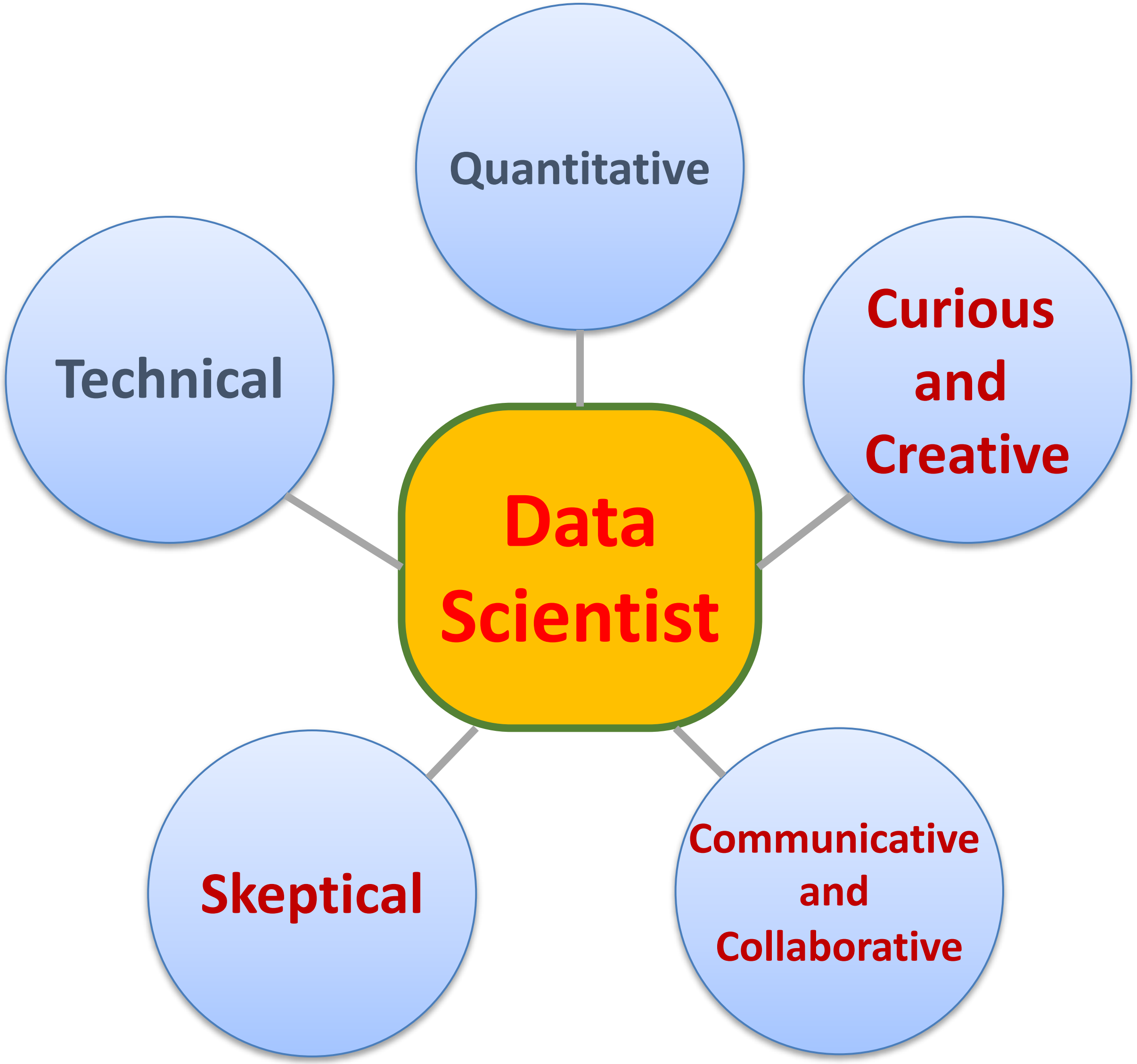
Source: EMC Education Services, Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data, Wiley, 2015

Profile of a Data Scientist

- Quantitative
  - mathematics or statistics
- Technical
  - software engineering, machine learning, and programming skills
- Skeptical mind-set and critical thinking
- Curious and creative
- Communicative and collaborative

Source: EMC Education Services, Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data, Wiley, 2015

Data Scientist Profile



Quantitative

Technical

Curious and Creative

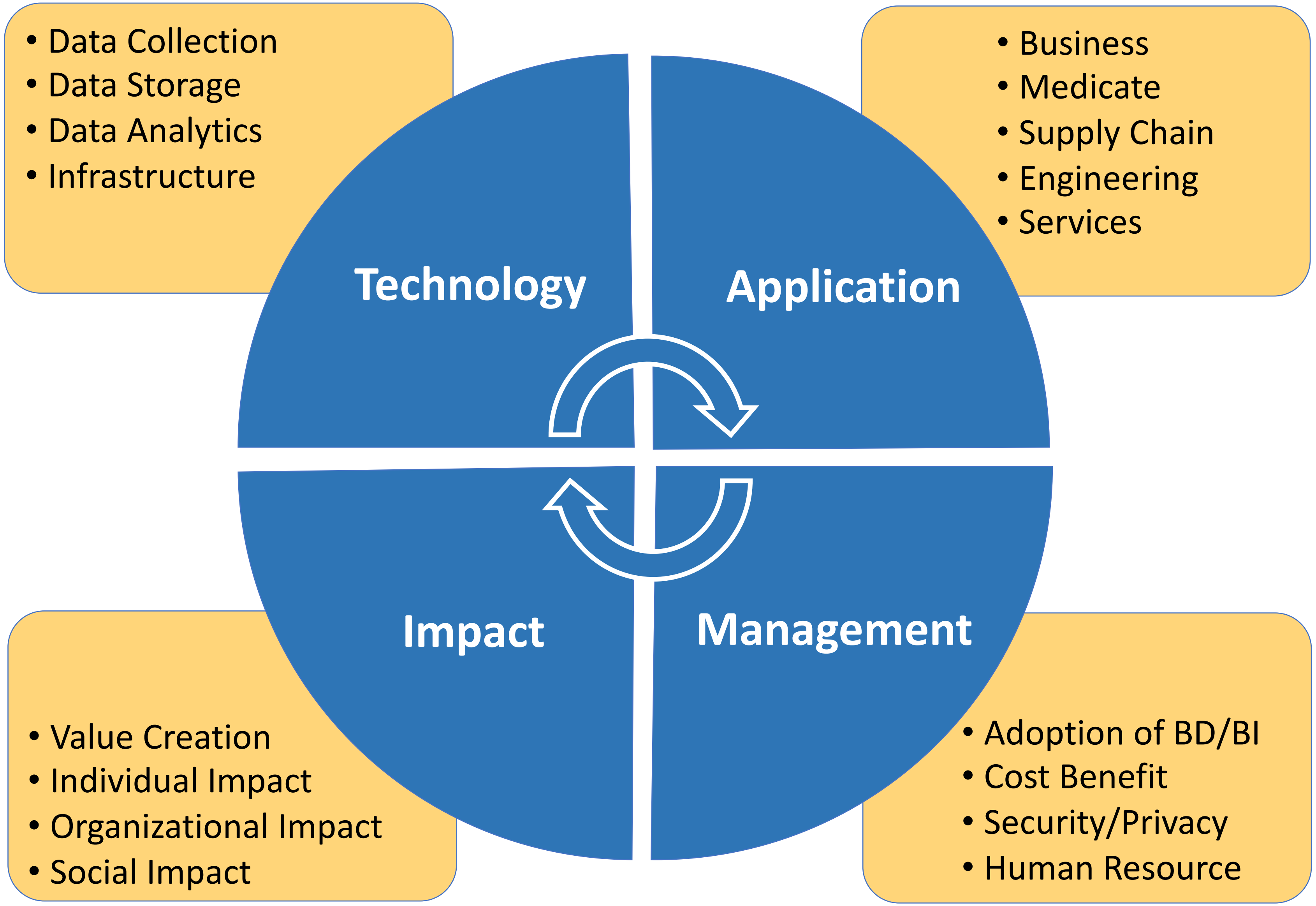
Data Scientist

Skeptical

Communicative and Collaborative

Source: EMC Education Services, Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data, Wiley, 2015

Framework for BD and BI Research



- Data Collection
- Data Storage
- Data Analytics
- Infrastructure

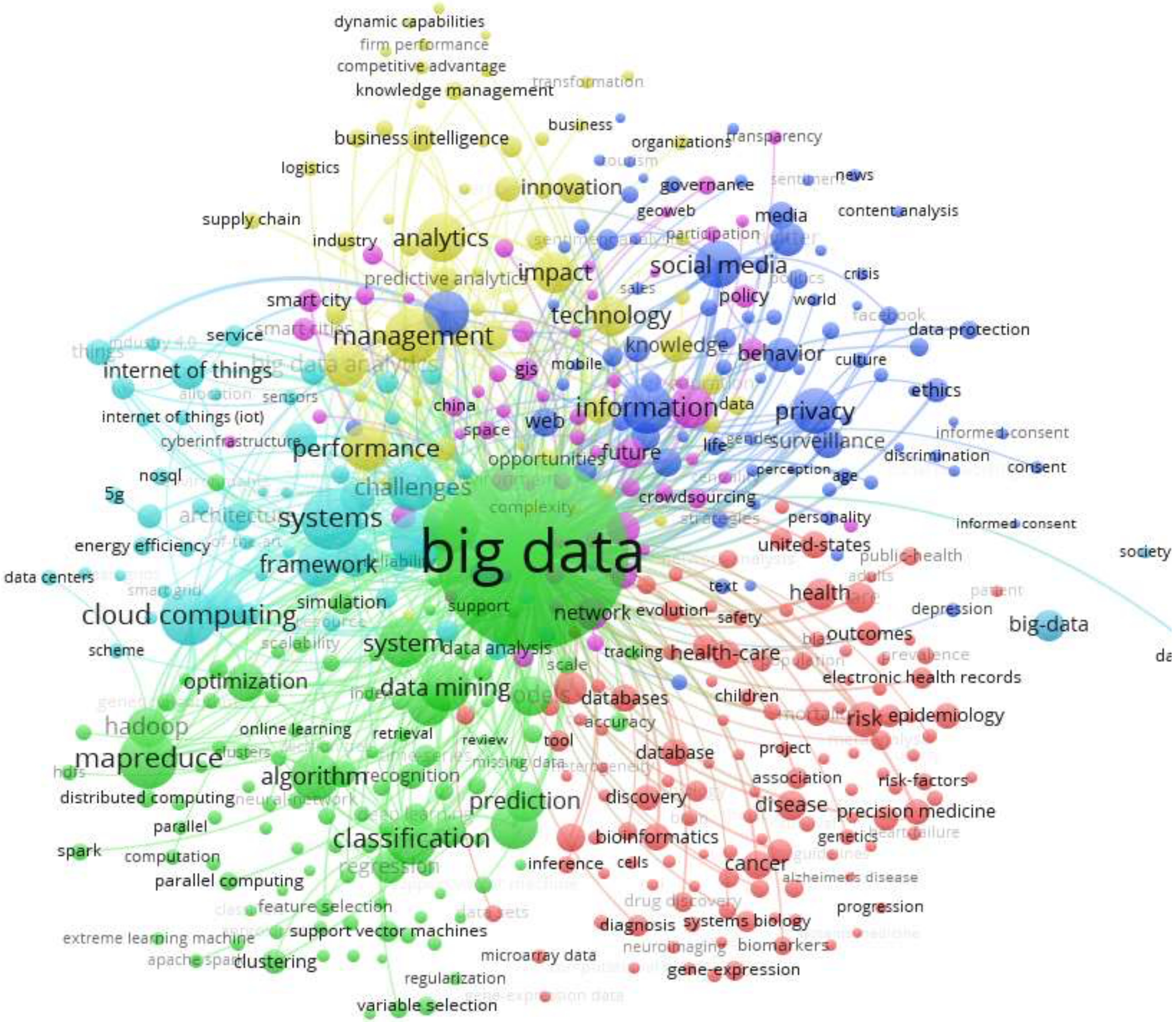
- Business
- Medicate
- Supply Chain
- Engineering
- Services

- Value Creation
- Individual Impact
- Organizational Impact
- Social Impact

- Adoption of BD/BI
- Cost Benefit
- Security/Privacy
- Human Resource

Source: Ting-Peng Liang and Yu-Hsi Liu (2018), "Research Landscape of Business Intelligence and Big Data analytics: A bibliometrics study", Expert Systems with Applications, Volume 111, 30, 2018, pp. 2-10

Business Intelligence and Big Data analytics



Source: Ting-Peng Liang and Yu-Hsi Liu (2018), "Research Landscape of Business Intelligence and Big Data analytics: A bibliometrics study", Expert Systems with Applications, Volume 111, 30, 2018, pp. 2-10

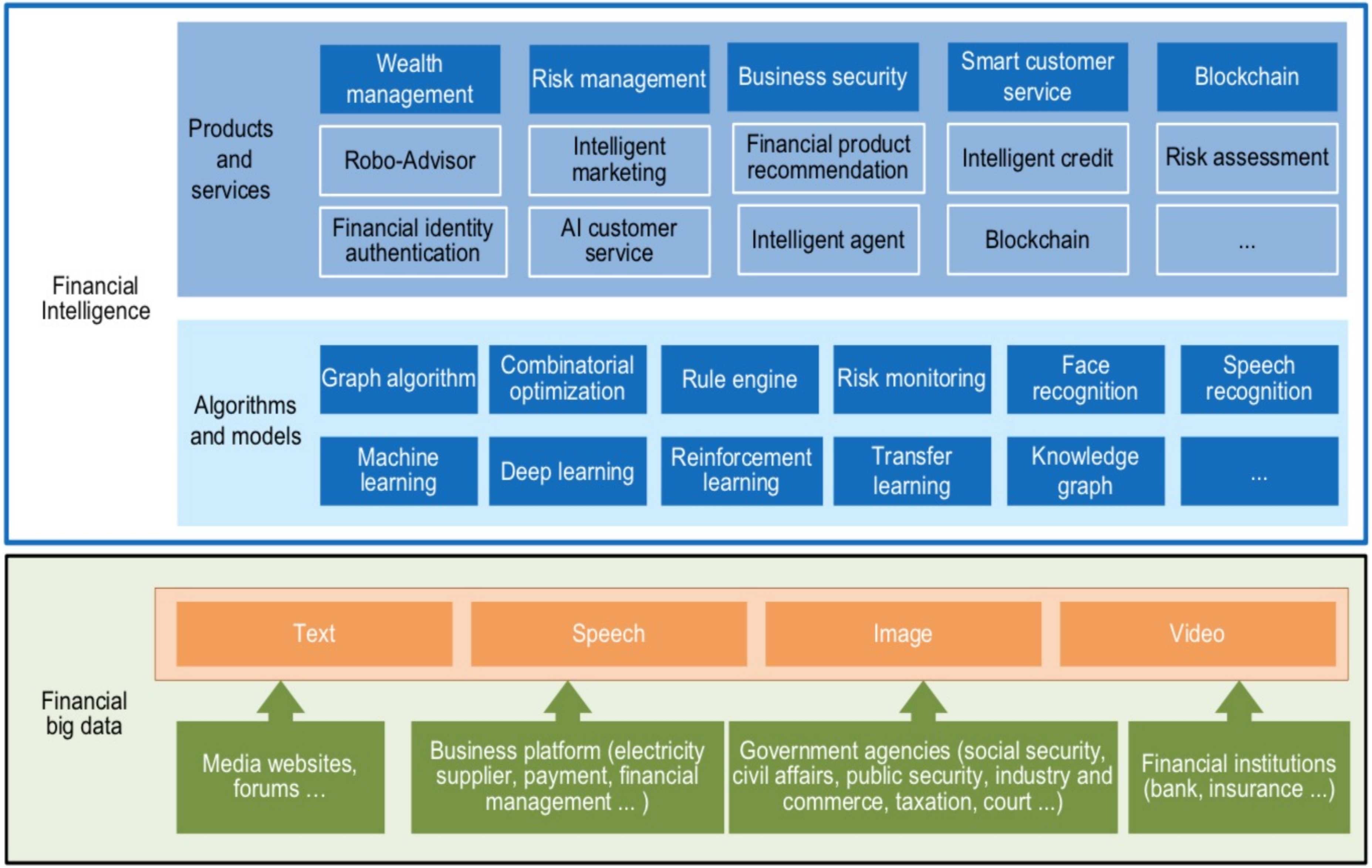
AI

in

FinTech

FinBrain: when Finance meets AI 2.0

(Zheng et al., 2019)



Financial Intelligence

Products and services

Wealth management

Risk management

Business security

Smart customer service

Blockchain

Robo-Advisor

Intelligent marketing

Financial product recommendation

Intelligent credit

Risk assessment

Financial identity authentication

AI customer service

Intelligent agent

Blockchain

...

Algorithms and models

Graph algorithm

Combinatorial optimization

Rule engine

Risk monitoring

Face recognition

Speech recognition

Machine learning

Deep learning

Reinforcement learning

Transfer learning

Knowledge graph

...

Financial big data

Text

Speech

Image

Video

Media websites, forums ...

Business platform (electricity supplier, payment, financial management ...)

Government agencies (social security, civil affairs, public security, industry and commerce, taxation, court ...)

Financial institutions (bank, insurance ...)

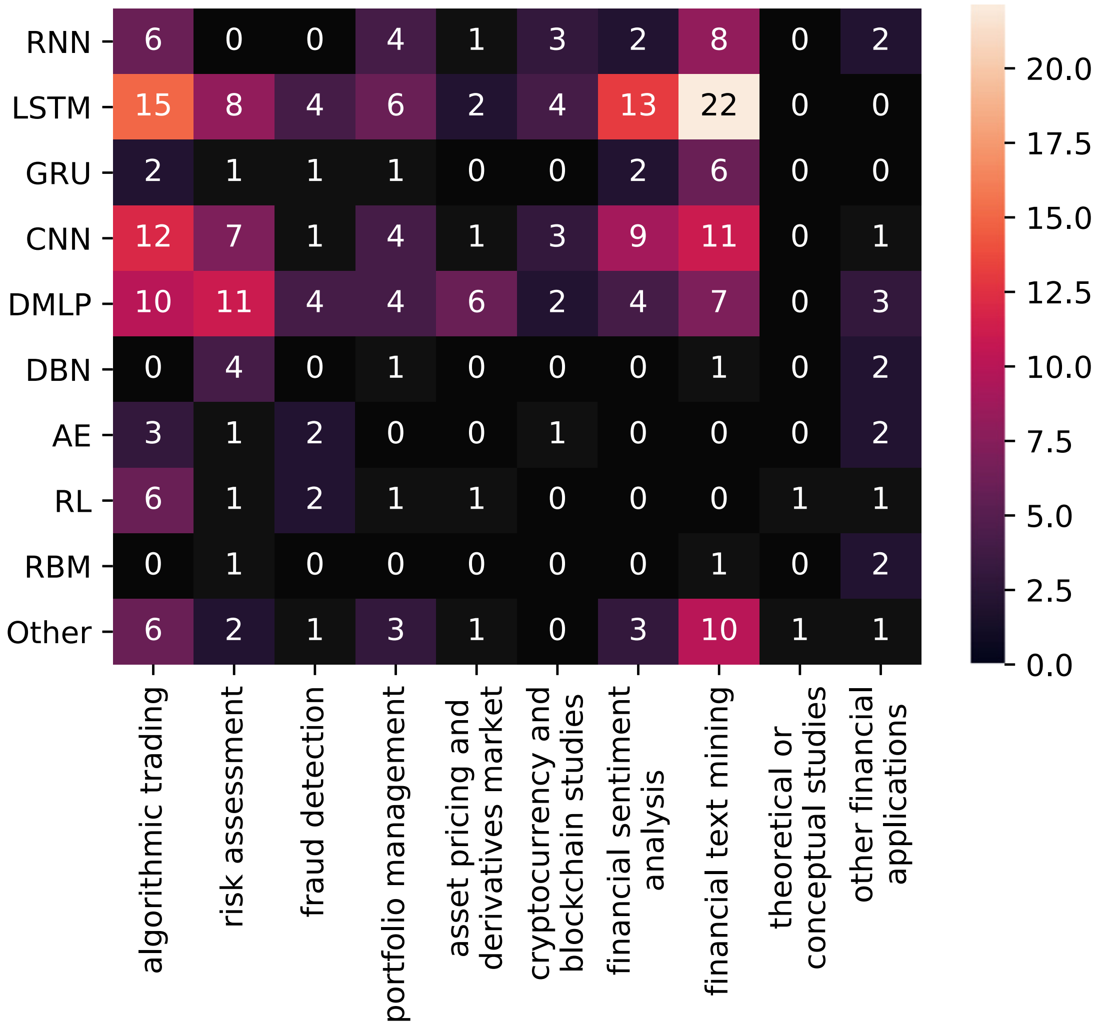
Source: Xiao-lin Zheng, Meng-ying Zhu, Qi-bing Li, Chao-chao Chen, and Yan-chao Tan (2019), "Finbrain: When finance meets AI 2.0." Frontiers of Information Technology & Electronic Engineering 20, no. 7, pp. 914-924

Technology-driven Financial Industry Development

Development stage	Driving technology	Main landscape	Inclusive finance	Relationship between technology and finance
Fintech 1.0 (financial IT)	Computer	Credit card, ATM, and CRMS	Low	Technology as a tool
Fintech 2.0 (Internet finance)	Mobile Internet	Marketplace lending, third-party payment, crowdfunding, and Internet insurance	Medium	Technology-driven change
Fintech 3.0 (financial intelligence)	AI, Big Data, Cloud Computing, Blockchain	Intelligent finance	High	Deep fusion

Source: Xiao-lin Zheng, Meng-ying Zhu, Qi-bing Li, Chao-chao Chen, and Yan-chao Tan (2019), "Finbrain: When finance meets AI 2.0." Frontiers of Information Technology & Electronic Engineering 20, no. 7, pp. 914-924

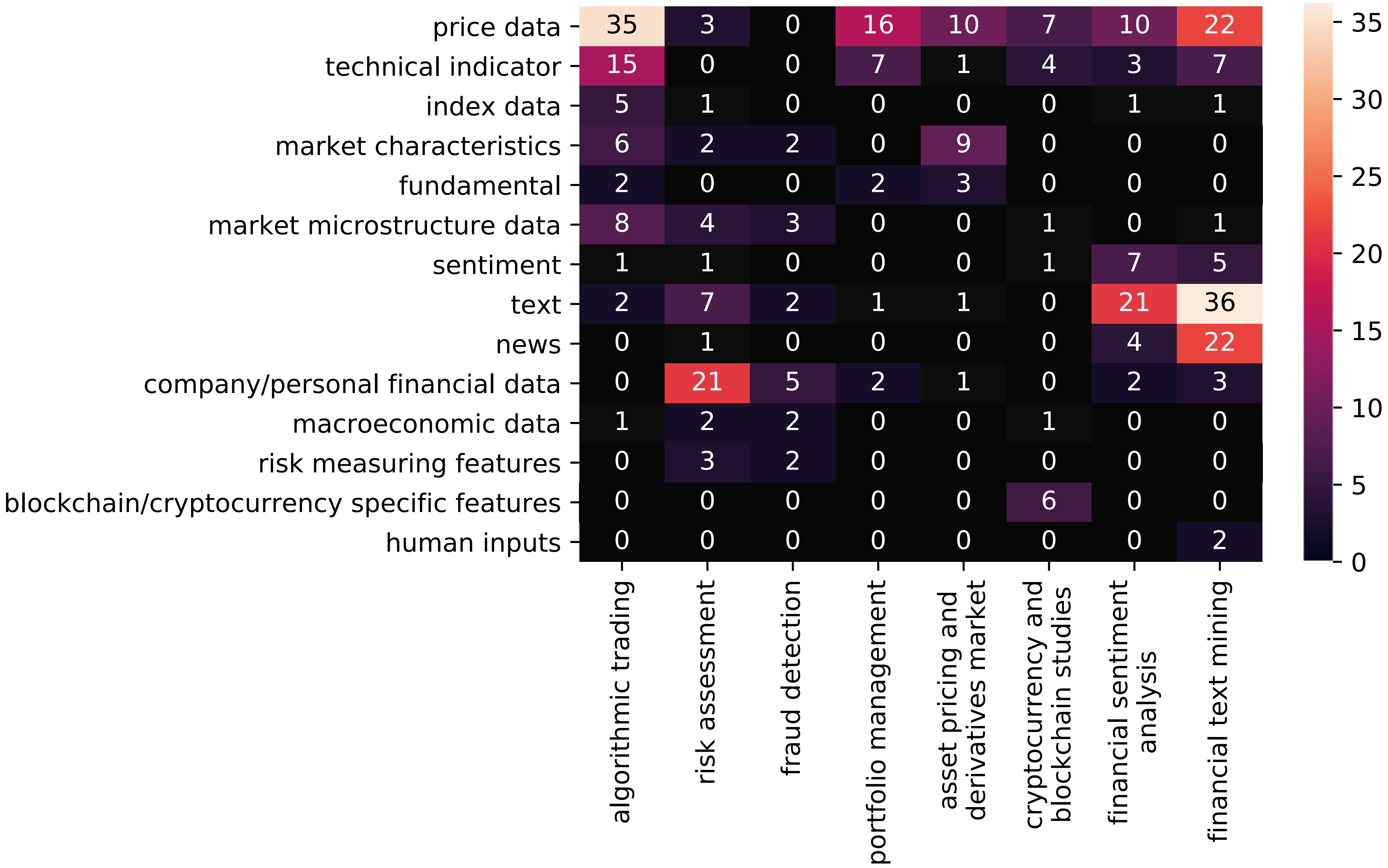
Deep learning for financial applications: Topic-Model Heatmap



	algorithmic trading	risk assessment	fraud detection	portfolio management	asset pricing and derivatives market	cryptocurrency and blockchain studies	financial sentiment analysis	financial text mining	theoretical or conceptual studies	other financial applications
RNN	6	0	0	4	1	3	2	8	0	2
LSTM	15	8	4	6	2	4	13	22	0	0
GRU	2	1	1	1	0	0	2	6	0	0
CNN	12	7	1	4	1	3	9	11	0	1
DMLP	10	11	4	4	6	2	4	7	0	3
DBN	0	4	0	1	0	0	0	1	0	2
AE	3	1	2	0	0	1	0	0	0	2
RL	6	1	2	1	1	0	0	0	1	1
RBM	0	1	0	0	0	0	0	1	0	2
Other	6	2	1	3	1	0	3	10	1	1

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

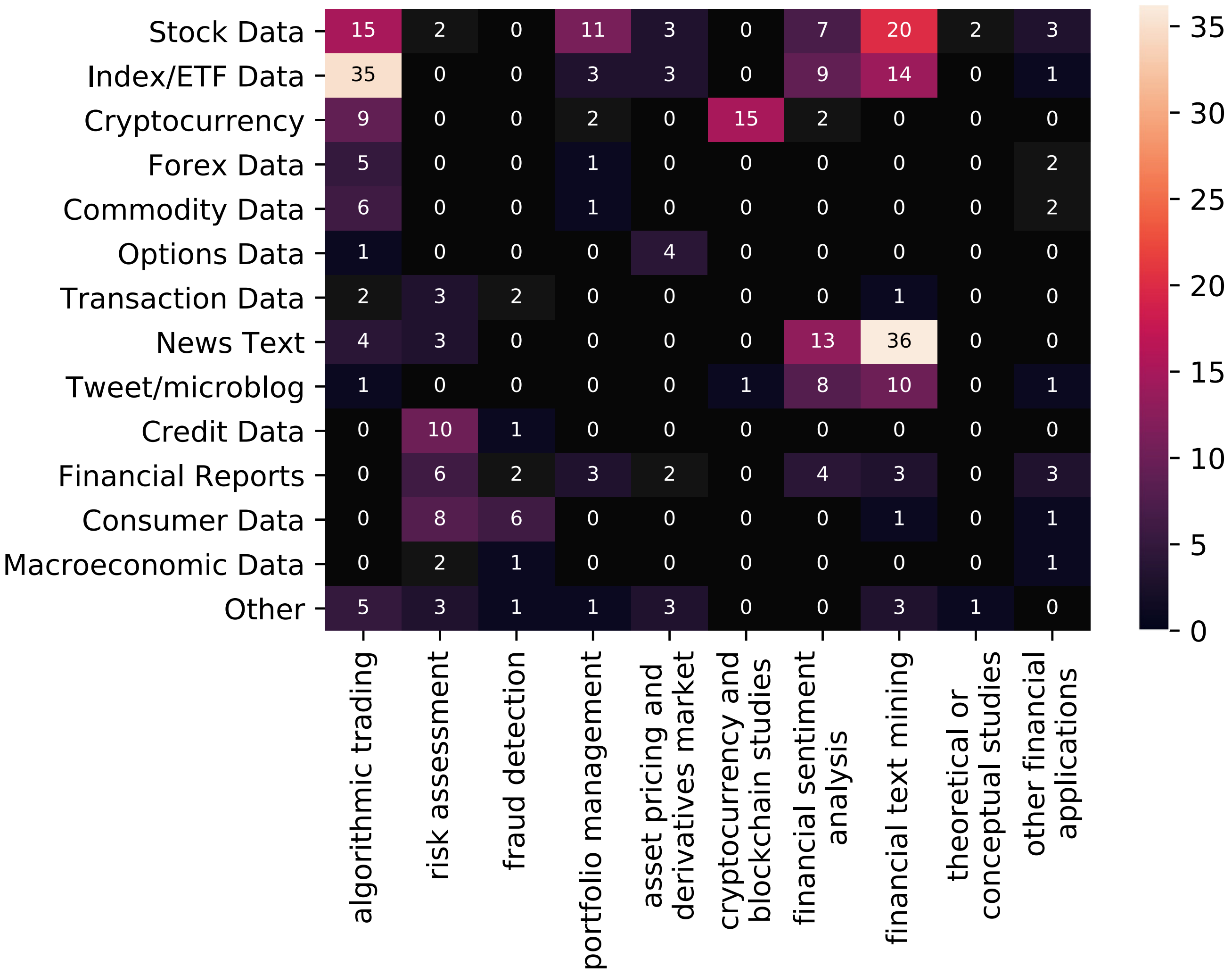
Deep learning for financial applications: Topic-Feature Heatmap



	algorithmic trading	risk assessment	fraud detection	portfolio management	asset pricing and derivatives market	cryptocurrency and blockchain studies	financial sentiment analysis	financial text mining
price data	35	3	0	16	10	7	10	22
technical indicator	15	0	0	7	1	4	3	7
index data	5	1	0	0	0	0	1	1
market characteristics	6	2	2	0	9	0	0	0
fundamental	2	0	0	2	3	0	0	0
market microstructure data	8	4	3	0	0	1	0	1
sentiment	1	1	0	0	0	1	7	5
text	2	7	2	1	1	0	21	36
news	0	1	0	0	0	0	4	22
company/personal financial data	0	21	5	2	1	0	2	3
macroeconomic data	1	2	2	0	0	1	0	0
risk measuring features	0	3	2	0	0	0	0	0
blockchain/cryptocurrency specific features	0	0	0	0	0	6	0	0
human inputs	0	0	0	0	0	0	0	2

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications: Topic-Dataset Heatmap



	algorithmic trading	risk assessment	fraud detection	portfolio management	asset pricing and derivatives market	cryptocurrency and blockchain studies	financial sentiment analysis	financial text mining	theoretical or conceptual studies	other financial applications
Stock Data	15	2	0	11	3	0	7	20	2	3
Index/ETF Data	35	0	0	3	3	0	9	14	0	1
Cryptocurrency	9	0	0	2	0	15	2	0	0	0
Forex Data	5	0	0	1	0	0	0	0	0	2
Commodity Data	6	0	0	1	0	0	0	0	0	2
Options Data	1	0	0	0	4	0	0	0	0	0
Transaction Data	2	3	2	0	0	0	0	1	0	0
News Text	4	3	0	0	0	0	13	36	0	0
Tweet/microblog	1	0	0	0	0	1	8	10	0	1
Credit Data	0	10	1	0	0	0	0	0	0	0
Financial Reports	0	6	2	3	2	0	4	3	0	3
Consumer Data	0	8	6	0	0	0	0	1	0	1
Macroeconomic Data	0	2	1	0	0	0	0	0	0	1
Other	5	3	1	1	3	0	0	3	1	0

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

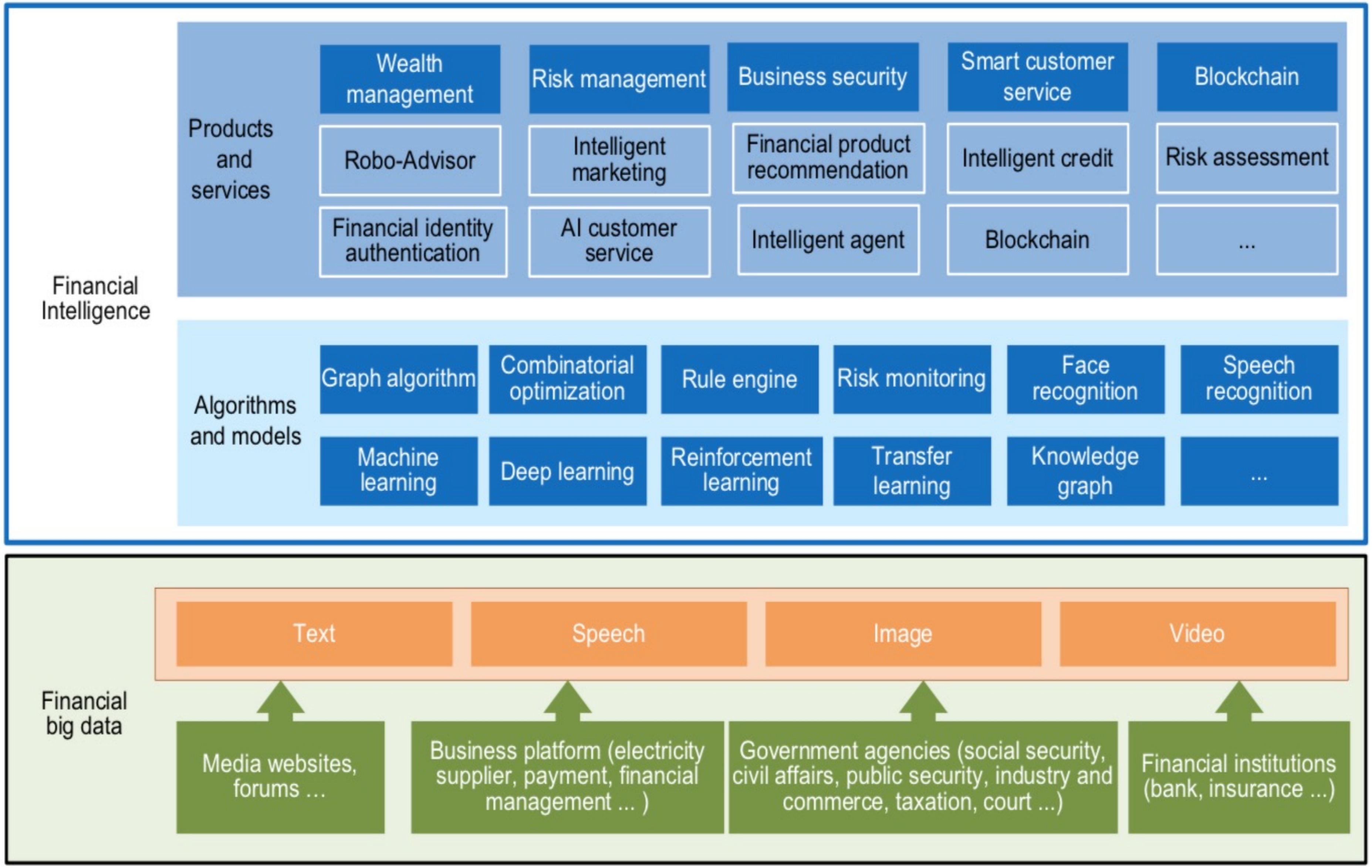
AI 2.0

a new generation of AI
based on the
novel information environment of
major changes and
the development of
new goals.

Yunhe Pan (2016), "Heading toward artificial intelligence 2.0." Engineering 2, no. 4, 409-413.

FinBrain: when Finance meets AI 2.0

(Zheng et al., 2019)



Source: Xiao-lin Zheng, Meng-ying Zhu, Qi-bing Li, Chao-chao Chen, and Yan-chao Tan (2019), "Finbrain: When finance meets AI 2.0."
Frontiers of Information Technology & Electronic Engineering 20, no. 7, pp. 914-924

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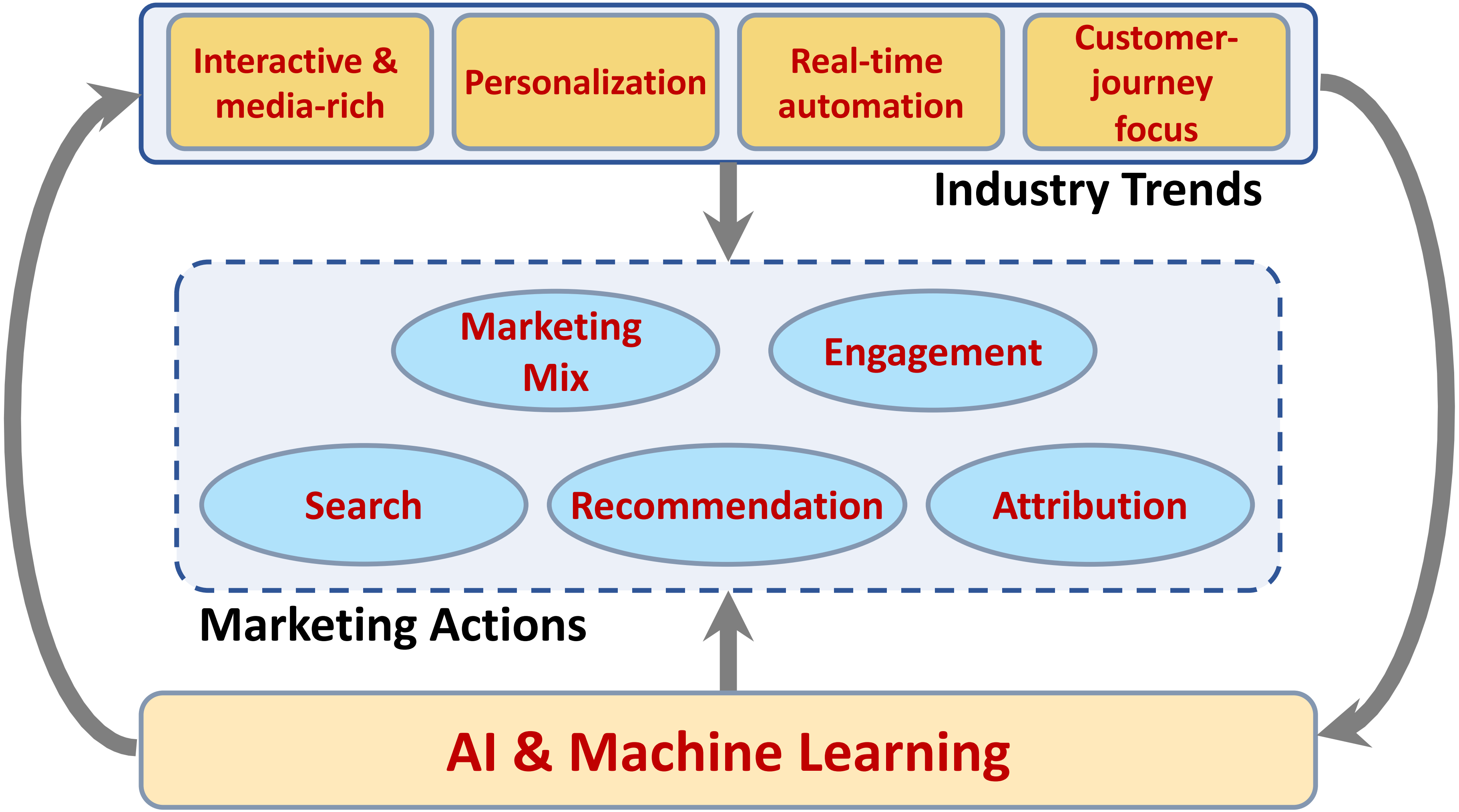
AI-driven Marketing

(Ma and Sun, 2020)



Interactive & media-rich

Personalization

Real-time automation

Customer-journey focus

Industry Trends

Marketing Mix

Engagement

Search

Recommendation

Attribution

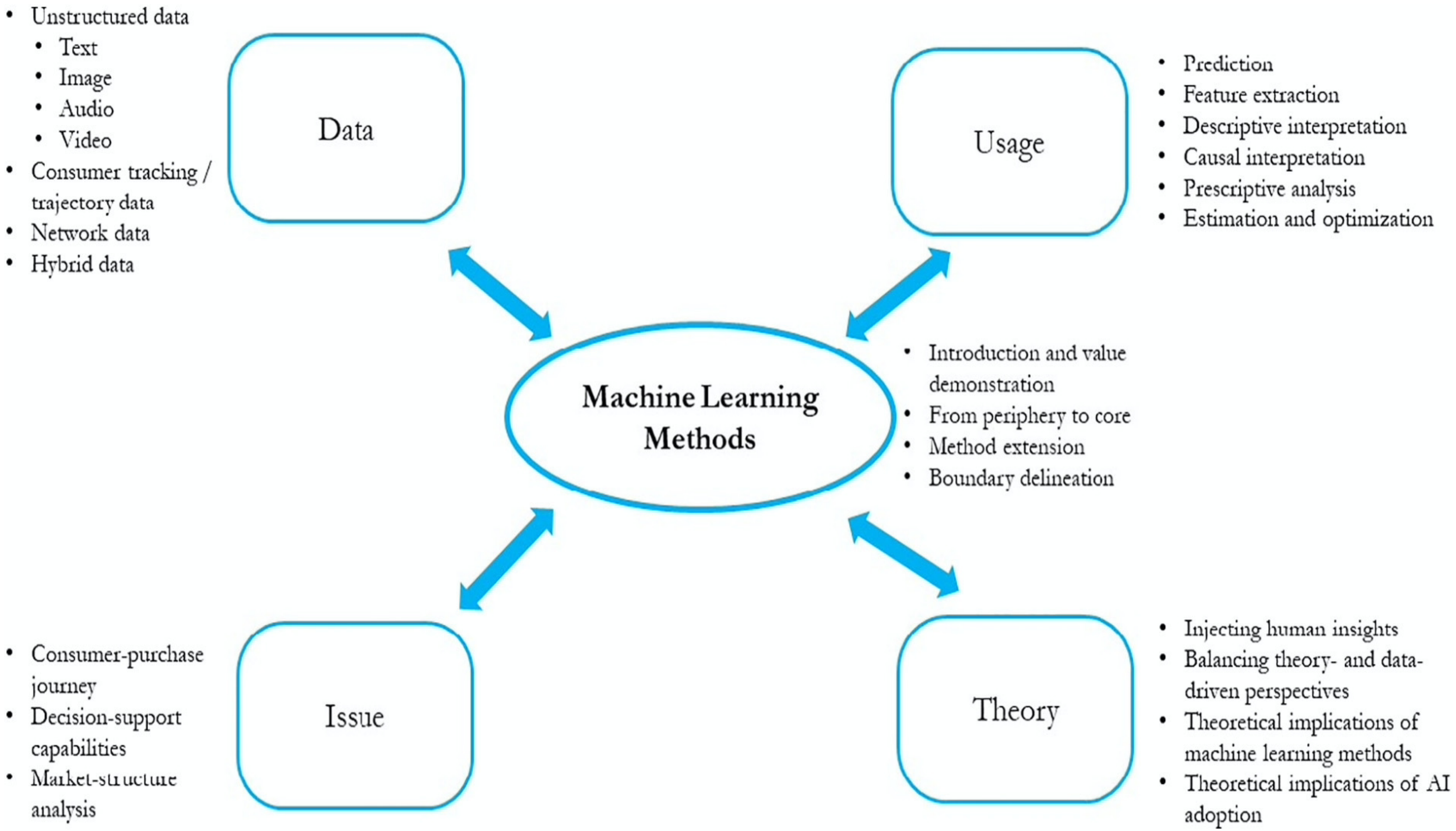
Marketing Actions

AI & Machine Learning

Source: Liye Ma and Baohong Sun (2020), "Machine learning and AI in marketing – Connecting computing power to human insights." International Journal of Research in Marketing, 37, no. 3, 481-504.

Machine Learning in Marketing Research

(Ma and Sun, 2020)



Data

- Unstructured data
  - Text
  - Image
  - Audio
  - Video
- Consumer tracking / trajectory data
- Network data
- Hybrid data

Usage

- Prediction
- Feature extraction
- Descriptive interpretation
- Causal interpretation
- Prescriptive analysis
- Estimation and optimization

Machine Learning Methods

- Introduction and value demonstration
- From periphery to core
- Method extension
- Boundary delineation

Issue

- Consumer-purchase journey
- Decision-support capabilities
- Market-structure analysis

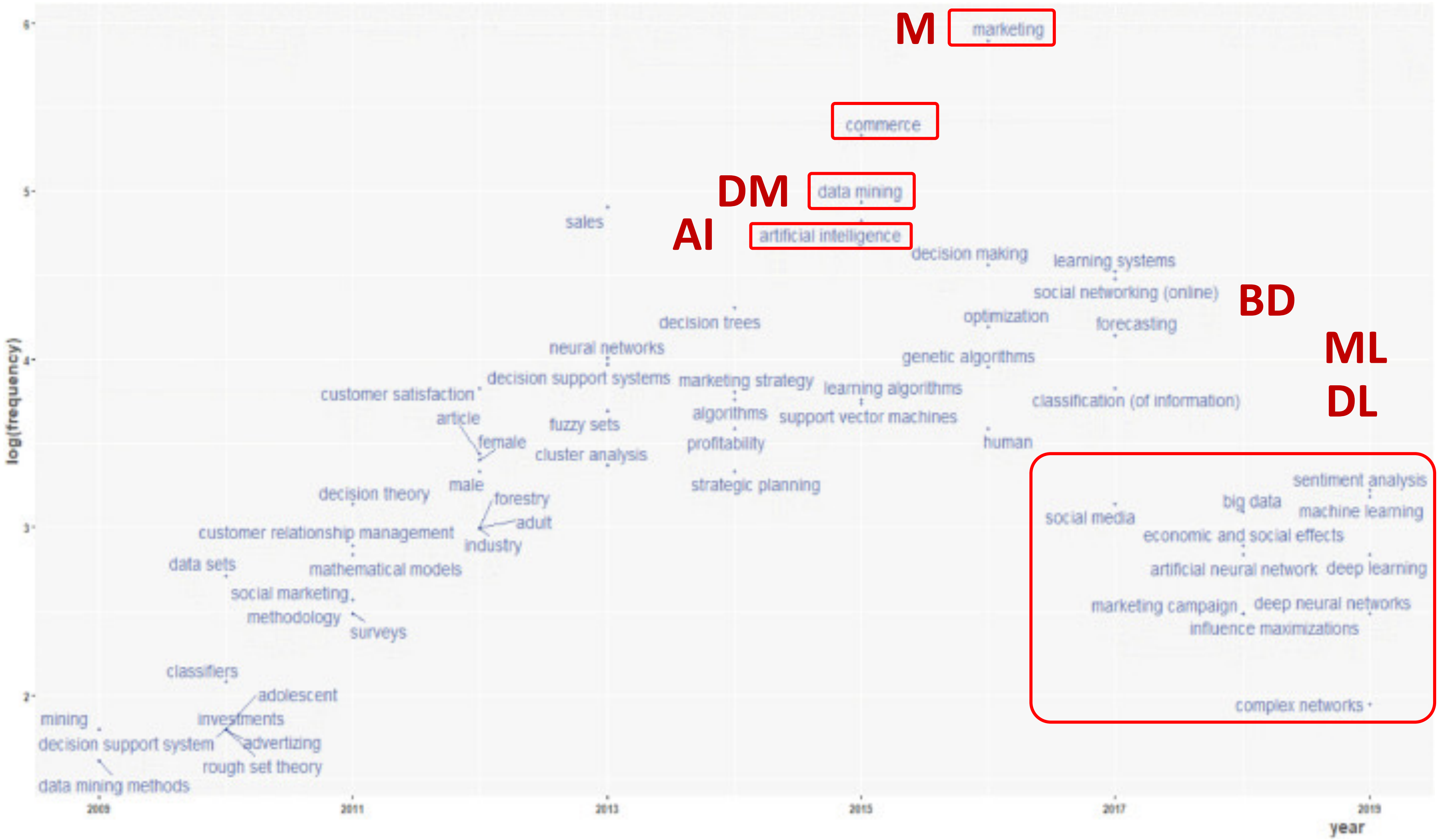
Theory

- Injecting human insights
- Balancing theory- and data-driven perspectives
- Theoretical implications of machine learning methods
- Theoretical implications of AI adoption

Source: Liye Ma and Baohong Sun (2020), "Machine learning and AI in marketing – Connecting computing power to human insights." International Journal of Research in Marketing, 37, no. 3, 481-504.

Artificial Intelligence in Marketing

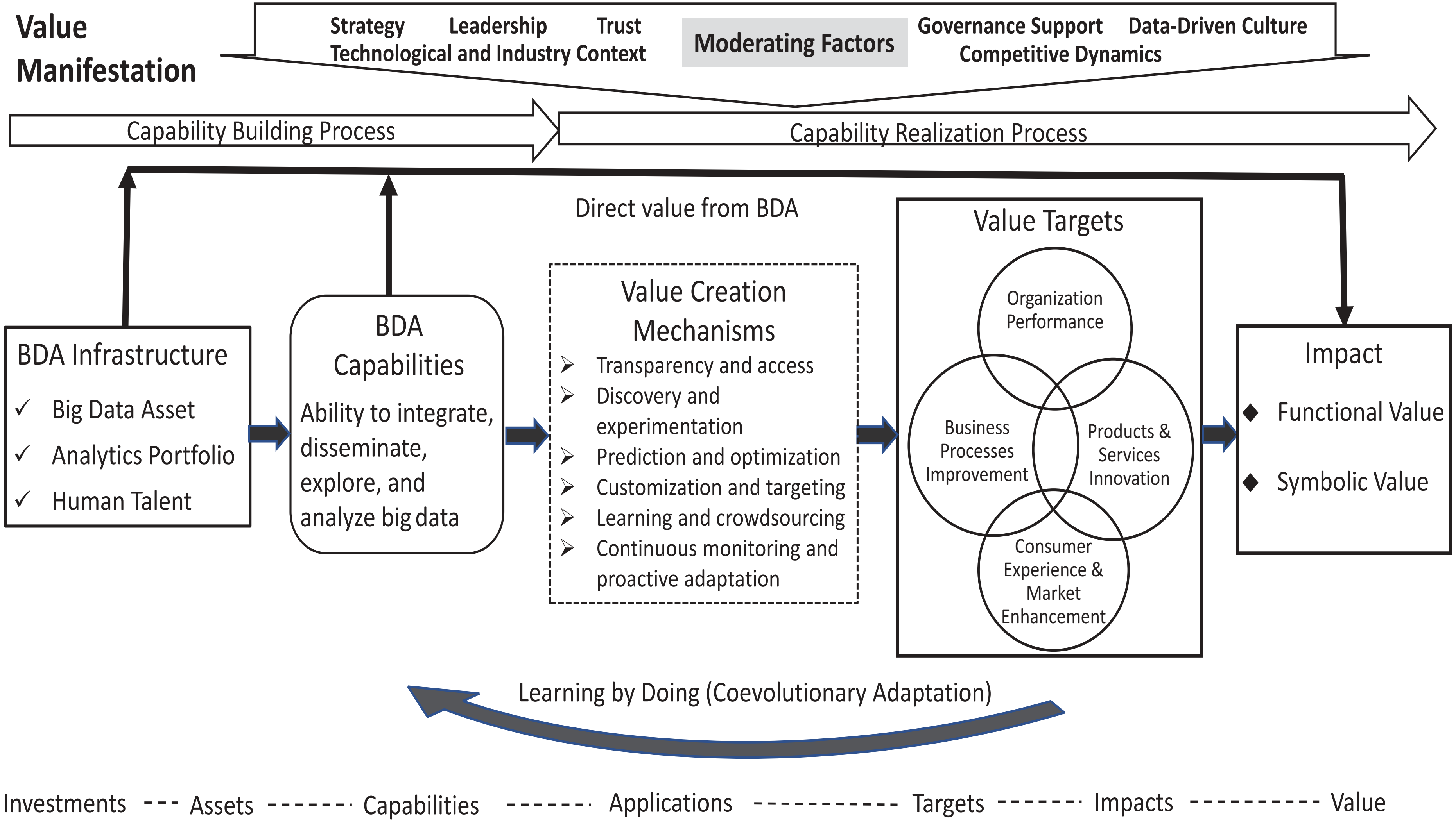
(Verma et al., 2021)



Source: Sanjeev Verma, Rohit Sharma, Subhamay Deb, and Debojit Maitra (2021),. "Artificial intelligence in marketing: Systematic review and future research direction." International Journal of Information Management Data Insights (2021): 100002.

Value Creation by Big Data Analytics

(Grover et al., 2018)



Source: Varun Grover, Roger HL Chiang, Ting-Peng Liang, and Dongsong Zhang (2018), "Creating Strategic Business Value from Big Data Analytics: A Research Framework", Journal of Management Information Systems, 35, no. 2, pp. 388-423.

Evolution of top keywords in “BD & BI” publications

2014

- Management
- Text Mining
- Data Mining
- Data Science

2015

- Big Data Analytics
- Social Media
- Business Analytics
- Information System

2016

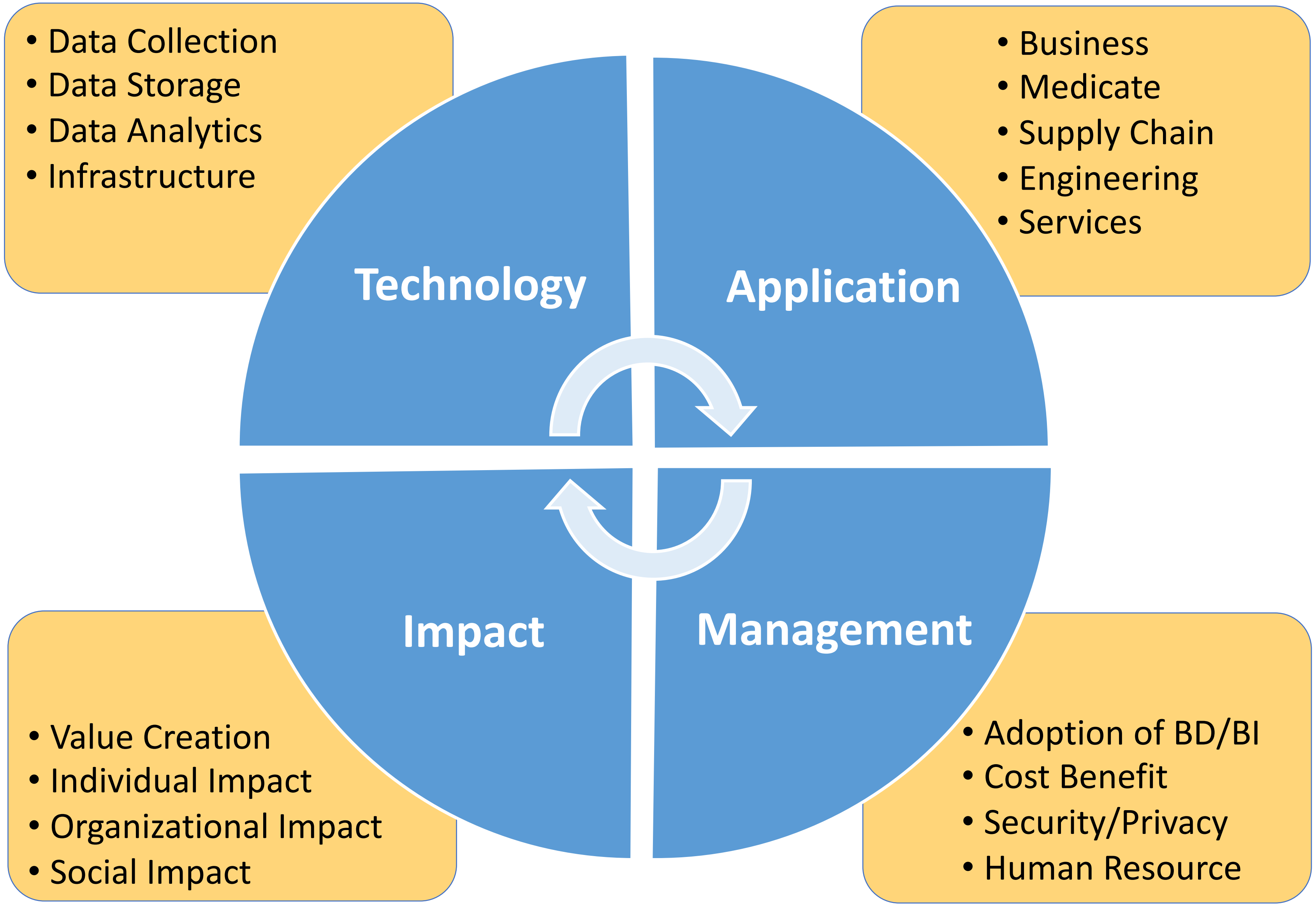
- Cloud Computing
- Data Warehouse

2017

- Knowledge Management

Source: Ting-Peng Liang and Yu-Hsi Liu (2018), "Research Landscape of Business Intelligence and Big Data analytics: A bibliometrics study”, Expert Systems with Applications, Volume 111, 30, 2018, pp. 2-10

Framework for BD and BI Research



- Data Collection
- Data Storage
- Data Analytics
- Infrastructure

Technology

- Business
- Medicate
- Supply Chain
- Engineering
- Services

Application

Impact

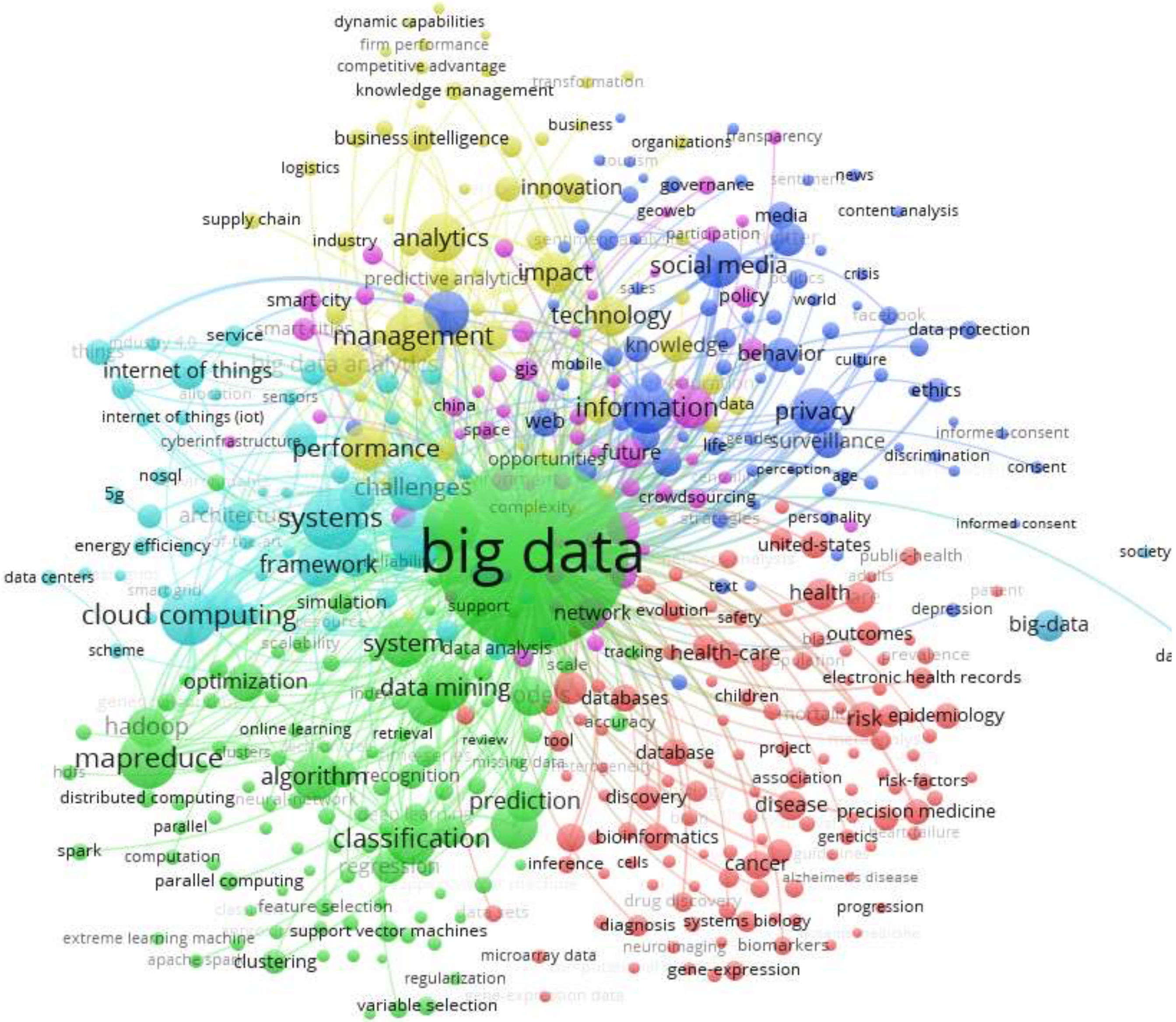
- Value Creation
- Individual Impact
- Organizational Impact
- Social Impact

Management

- Adoption of BD/BI
- Cost Benefit
- Security/Privacy
- Human Resource

Source: Ting-Peng Liang and Yu-Hsi Liu (2018), "Research Landscape of Business Intelligence and Big Data analytics: A bibliometrics study”, Expert Systems with Applications, Volume 111, 30, 2018, pp. 2-10

Business Intelligence and Big Data analytics



Source: Ting-Peng Liang and Yu-Hsi Liu (2018), "Research Landscape of Business Intelligence and Big Data analytics: A bibliometrics study", Expert Systems with Applications, Volume 111, 30, 2018, pp. 2-10

Deep learning for financial applications: A survey

Applied Soft Computing (2020)

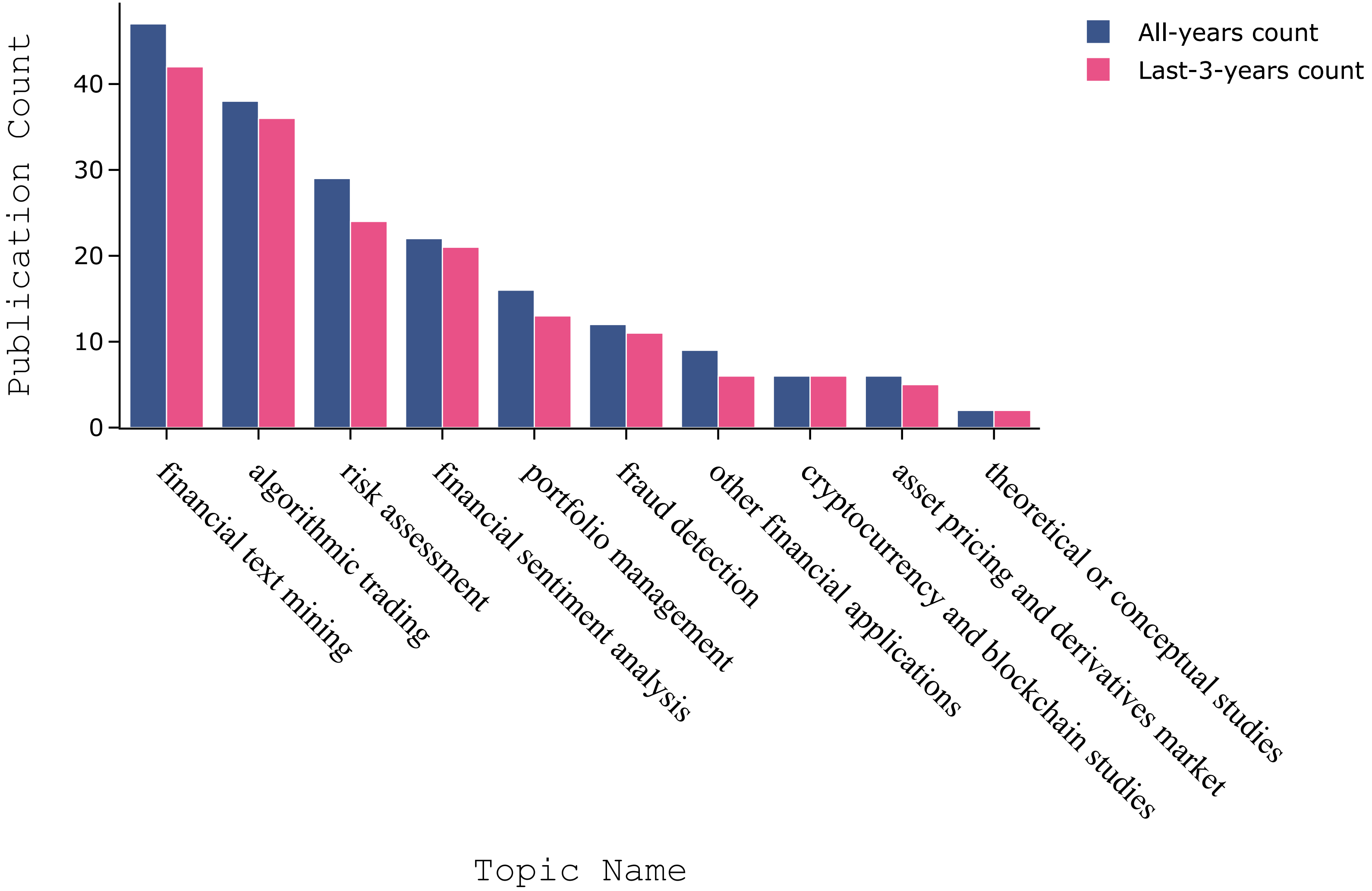
Source:
Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey."
Applied Soft Computing (2020): 106384.

Financial
time series forecasting with
deep learning:
A systematic literature review:
2005–2019

Applied Soft Computing (2020)

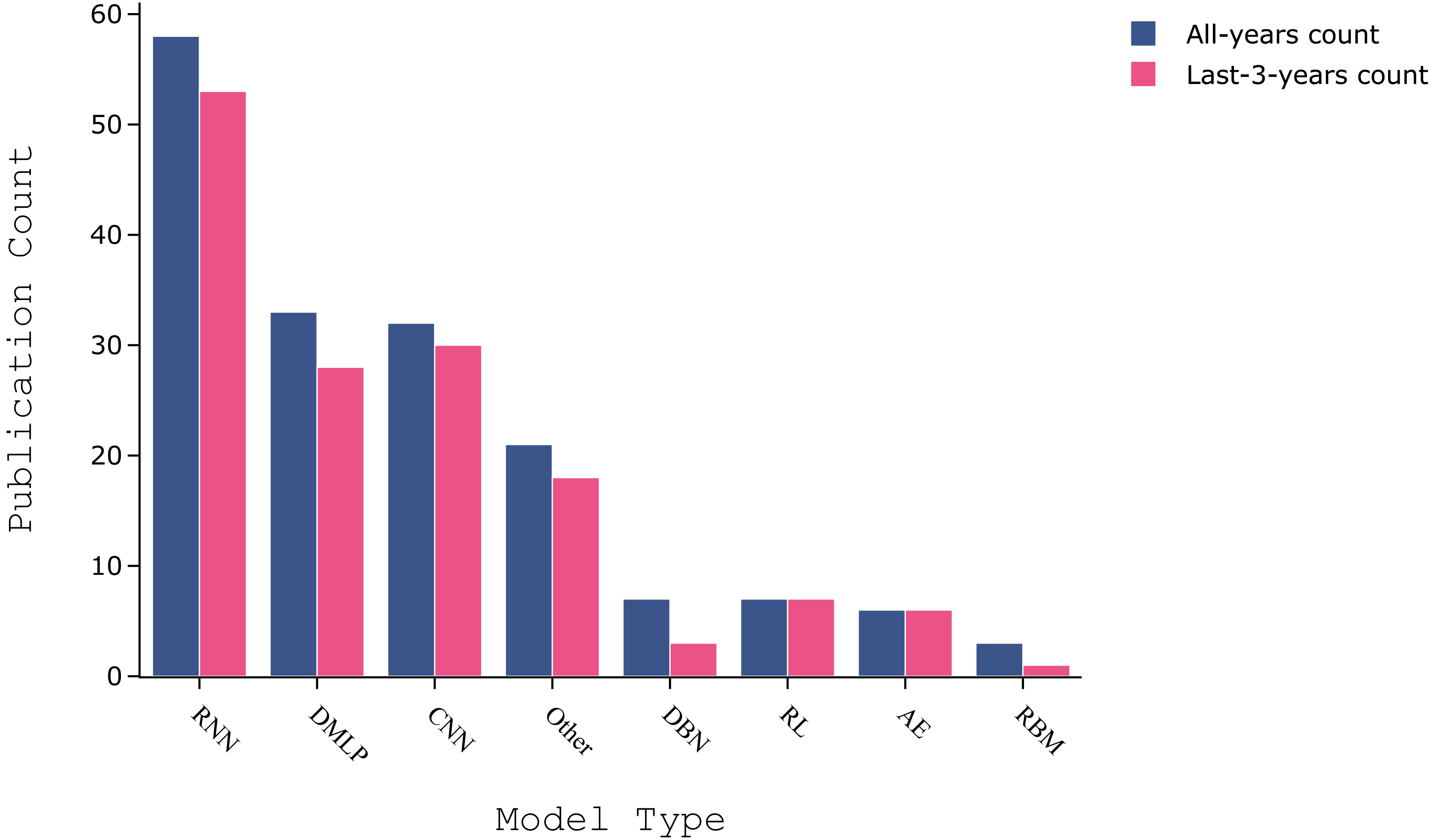
Source:
Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020),
"Financial time series forecasting with deep learning: A systematic literature review:
2005–2019." Applied Soft Computing 90 (2020): 106181.

Deep learning for financial applications: Topics



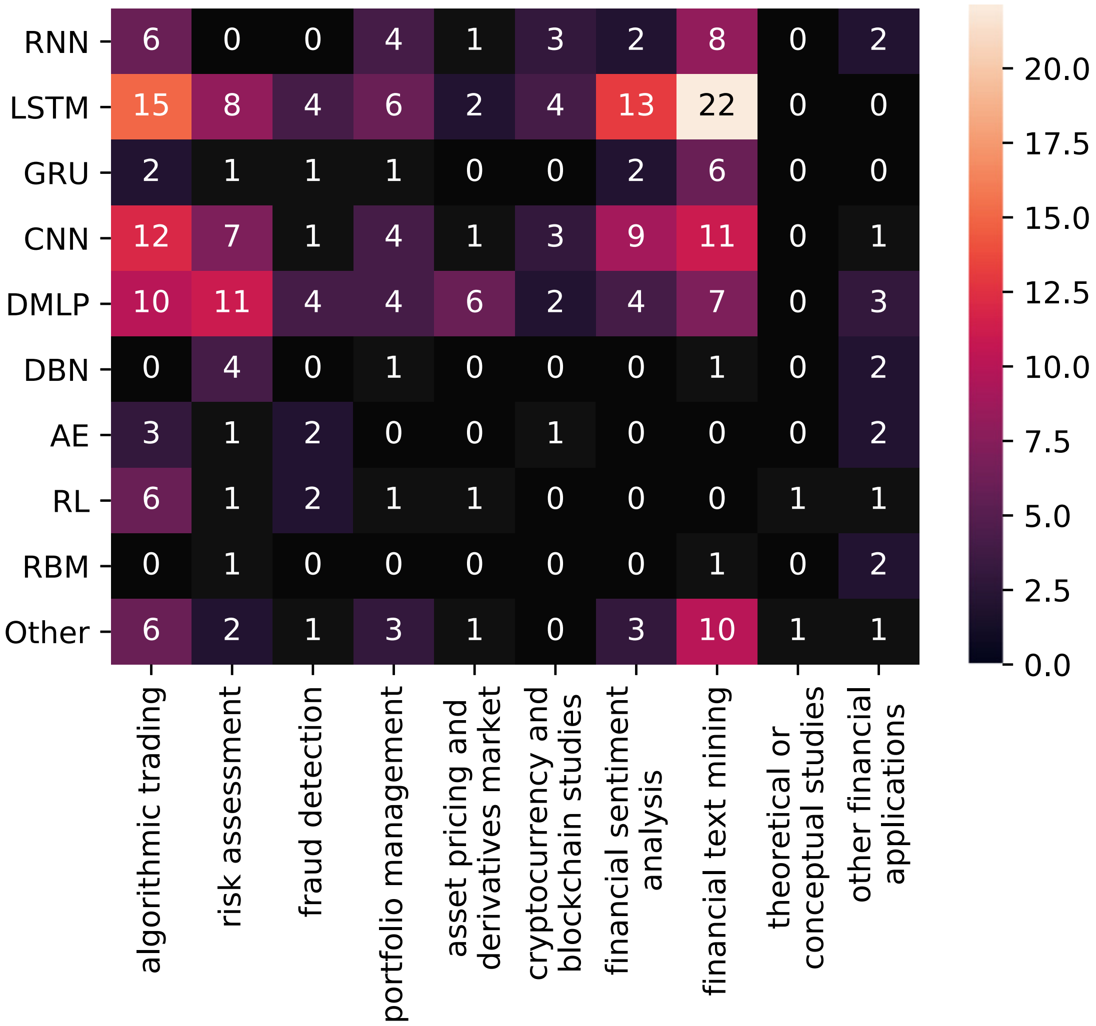
Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications: Deep Learning Models



Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

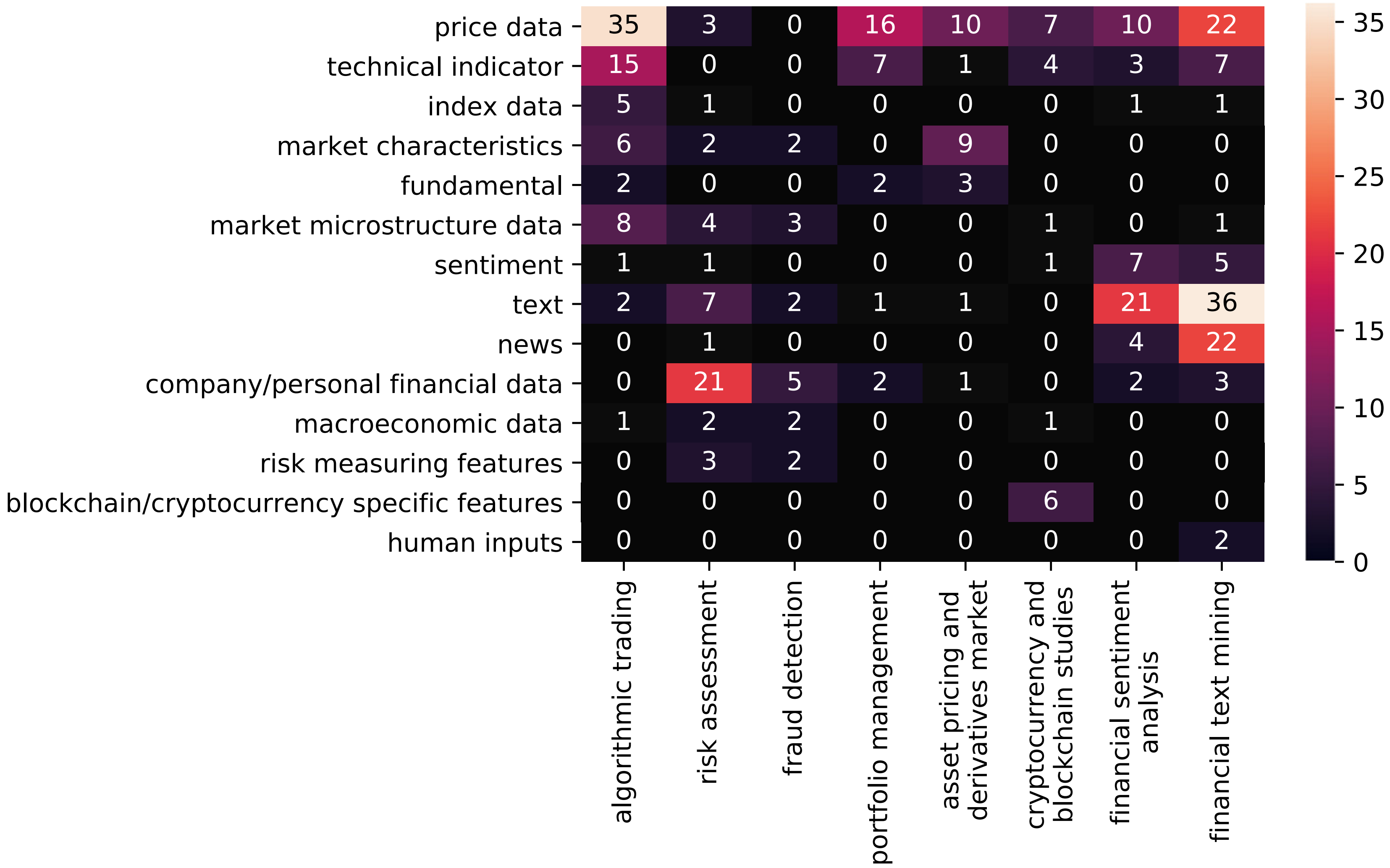
Deep learning for financial applications: Topic-Model Heatmap



	algorithmic trading	risk assessment	fraud detection	portfolio management	asset pricing and derivatives market	cryptocurrency and blockchain studies	financial sentiment analysis	financial text mining	theoretical or conceptual studies	other financial applications
RNN	6	0	0	4	1	3	2	8	0	2
LSTM	15	8	4	6	2	4	13	22	0	0
GRU	2	1	1	1	0	0	2	6	0	0
CNN	12	7	1	4	1	3	9	11	0	1
DMLP	10	11	4	4	6	2	4	7	0	3
DBN	0	4	0	1	0	0	0	1	0	2
AE	3	1	2	0	0	1	0	0	0	2
RL	6	1	2	1	1	0	0	0	1	1
RBM	0	1	0	0	0	0	0	1	0	2
Other	6	2	1	3	1	0	3	10	1	1

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

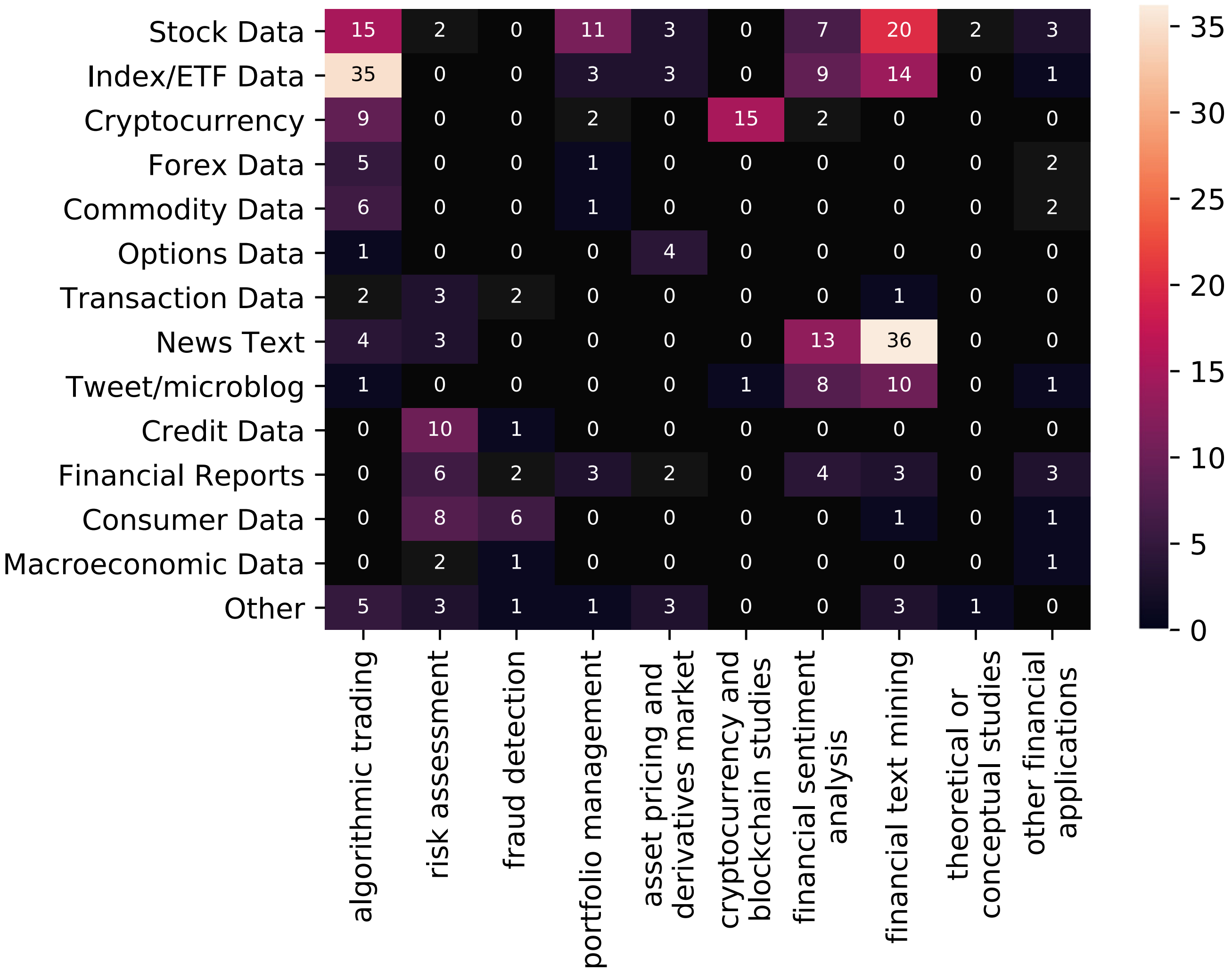
Deep learning for financial applications: Topic-Feature Heatmap



	algorithmic trading	risk assessment	fraud detection	portfolio management	asset pricing and derivatives market	cryptocurrency and blockchain studies	financial sentiment analysis	financial text mining
price data	35	3	0	16	10	7	10	22
technical indicator	15	0	0	7	1	4	3	7
index data	5	1	0	0	0	0	1	1
market characteristics	6	2	2	0	9	0	0	0
fundamental	2	0	0	2	3	0	0	0
market microstructure data	8	4	3	0	0	1	0	1
sentiment	1	1	0	0	0	1	7	5
text	2	7	2	1	1	0	21	36
news	0	1	0	0	0	0	4	22
company/personal financial data	0	21	5	2	1	0	2	3
macroeconomic data	1	2	2	0	0	1	0	0
risk measuring features	0	3	2	0	0	0	0	0
blockchain/cryptocurrency specific features	0	0	0	0	0	6	0	0
human inputs	0	0	0	0	0	0	0	2

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications: Topic-Dataset Heatmap



	algorithmic trading	risk assessment	fraud detection	portfolio management	asset pricing and derivatives market	cryptocurrency and blockchain studies	financial sentiment analysis	financial text mining	theoretical or conceptual studies	other financial applications
Stock Data	15	2	0	11	3	0	7	20	2	3
Index/ETF Data	35	0	0	3	3	0	9	14	0	1
Cryptocurrency	9	0	0	2	0	15	2	0	0	0
Forex Data	5	0	0	1	0	0	0	0	0	2
Commodity Data	6	0	0	1	0	0	0	0	0	2
Options Data	1	0	0	0	4	0	0	0	0	0
Transaction Data	2	3	2	0	0	0	0	1	0	0
News Text	4	3	0	0	0	0	13	36	0	0
Tweet/microblog	1	0	0	0	0	1	8	10	0	1
Credit Data	0	10	1	0	0	0	0	0	0	0
Financial Reports	0	6	2	3	2	0	4	3	0	3
Consumer Data	0	8	6	0	0	0	0	1	0	1
Macroeconomic Data	0	2	1	0	0	0	0	0	0	1
Other	5	3	1	1	3	0	0	3	1	0

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:

Algo-trading applications embedded with time series forecasting models

Art.	Data set	Period	Feature set	Method	Performance criteria	Environment
[33]	GarantiBank in BIST, Turkey	2016	OCHLV, Spread, Volatility, Turnover, etc.	PLR, Graves LSTM	MSE, RMSE, MAE, RSE, Correlation R-square	Spark
[34]	CSI300, Nifty50, HSI, Nikkei 225, S&P500, DJIA	2010–2016	OCHLV, Technical Indicators	WT, Stacked autoencoders, LSTM	MAPE, Correlation coefficient, THEIL-U	–
[35]	Chinese Stocks	2007–2017	OCHLV	CNN + LSTM	Annualized Return, Mxm Retracement	Python
[36]	50 stocks from NYSE	2007–2016	Price data	SFM	MSE	–
[37]	The LOB of 5 stocks of Finnish Stock Market	2010	FI-2010 dataset: bid/ask and volume	WMTR, MDA	Accuracy, Precision, Recall, F1-Score	–
[38]	300 stocks from SZSE, Commodity	2014–2015	Price data	FDDR, DMLP+RL	Profit, return, SR, profit-loss curves	Keras
[39]	S&P500 Index	1989–2005	Price data, Volume	LSTM	Return, STD, SR, Accuracy	Python, TensorFlow, Keras, R, H2O
[40]	Stock of National Bank of Greece (ETE).	2009–2014	FTSE100, DJIA, GDAX, NIKKEI225, EUR/USD, Gold	GASVR, LSTM	Return, volatility, SR, Accuracy	Tensorflow
[41]	Chinese stock-IF-IH-IC contract	2016–2017	Decisions for price change	MODRL+LSTM	Profit and loss, SR	–
[42]	Singapore Stock Market Index	2010–2017	OCHL of last 10 days of Index	DMLP	RMSE, MAPE, Profit, SR	–
[43]	GBP/USD	2017	Price data	Reinforcement Learning + LSTM + NES	SR, downside deviation ratio, total profit	Python, Keras, Tensorflow
[44]	Commodity, FX future, ETF	1991–2014	Price Data	DMLP	SR, capability ratio, return	C++, Python
[45]	USD/GBP, S&P500, FTSE100, oil, gold	2016	Price data	AE + CNN	SR, % volatility, avg return/trans, rate of return	H2O

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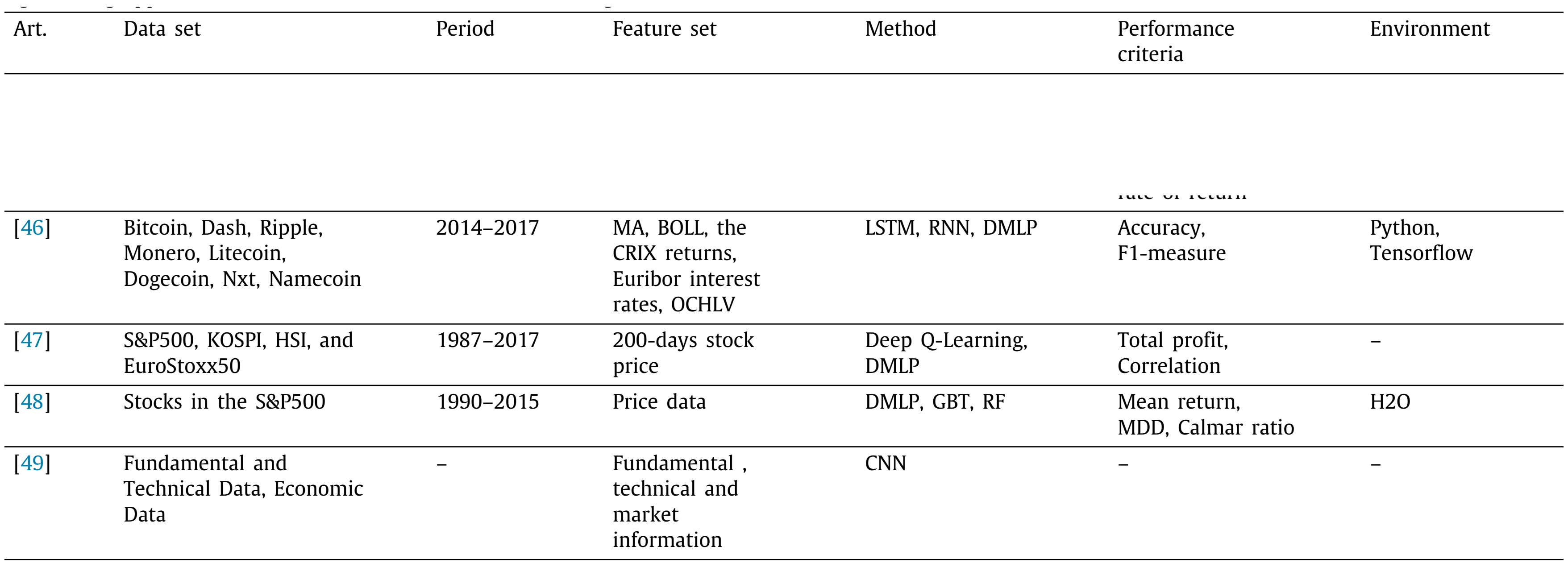
Deep learning for financial applications:

Algo-trading applications embedded with time series forecasting models



Art.	Data set	Period	Feature set	Method	Performance criteria	Environment
[46]	Bitcoin, Dash, Ripple, Monero, Litecoin, Dogecoin, Nxt, Namecoin	2014–2017	MA, BOLL, the CRIX returns, Euribor interest rates, OCHLV	LSTM, RNN, DMLP	Accuracy, F1-measure	Python, Tensorflow
[47]	S&P500, KOSPI, HSI, and EuroStoxx50	1987–2017	200-days stock price	Deep Q-Learning, DMLP	Total profit, Correlation	–
[48]	Stocks in the S&P500	1990–2015	Price data	DMLP, GBT, RF	Mean return, MDD, Calmar ratio	H2O
[49]	Fundamental and Technical Data, Economic Data	–	Fundamental , technical and market information	CNN	–	–

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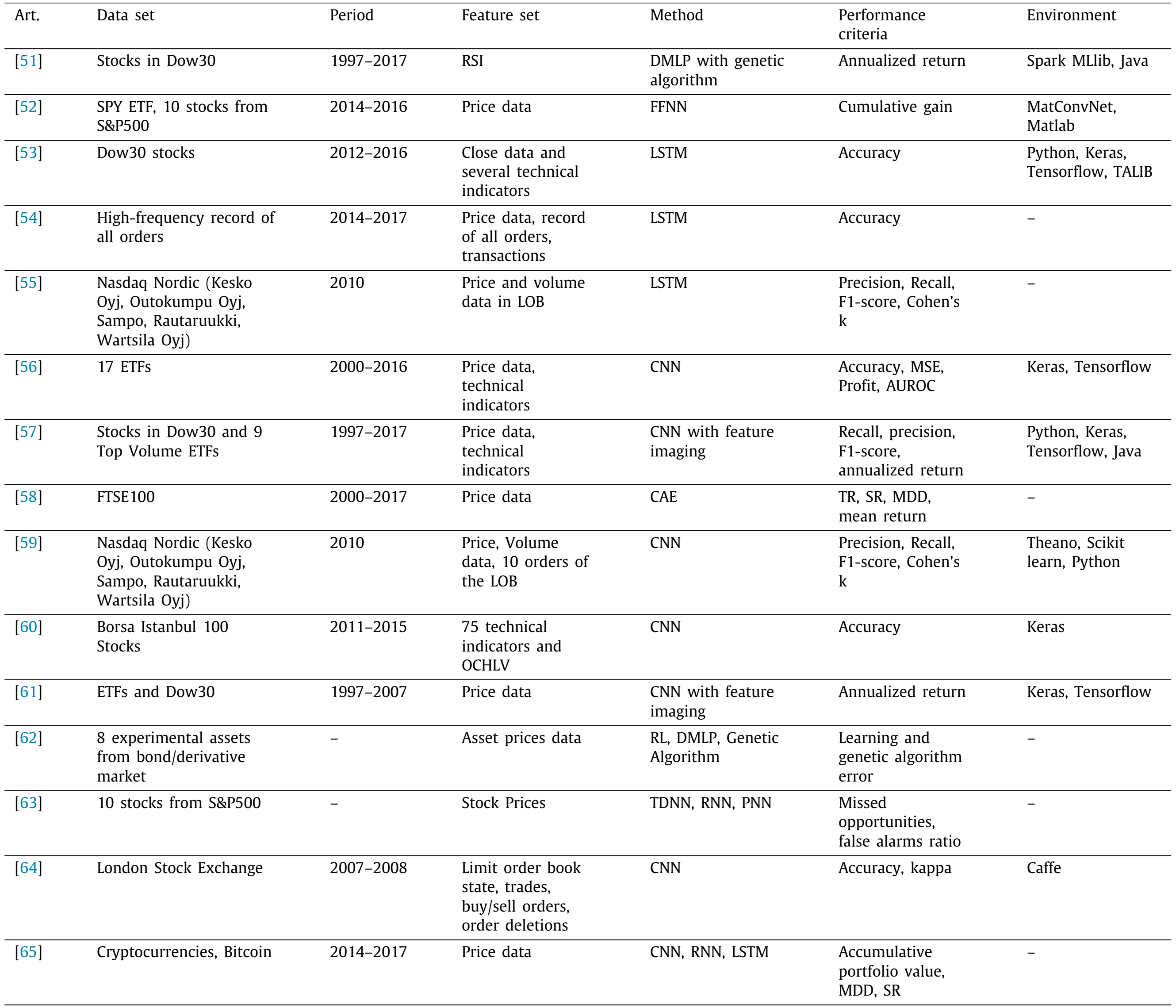
Deep learning for financial applications:

Classification (buy–sell signal, or trend detection) based algo-trading models



Art.	Data set	Period	Feature set	Method	Performance criteria	Environment
[51]	Stocks in Dow30	1997–2017	RSI	DMLP with genetic algorithm	Annualized return	Spark MLlib, Java
[52]	SPY ETF, 10 stocks from S&P500	2014–2016	Price data	FFNN	Cumulative gain	MatConvNet, Matlab
[53]	Dow30 stocks	2012–2016	Close data and several technical indicators	LSTM	Accuracy	Python, Keras, Tensorflow, TALIB
[54]	High-frequency record of all orders	2014–2017	Price data, record of all orders, transactions	LSTM	Accuracy	–
[55]	Nasdaq Nordic (Kesko Oyj, Outokumpu Oyj, Sampo, Rautaruukki, Wartsila Oyj)	2010	Price and volume data in LOB	LSTM	Precision, Recall, F1-score, Cohen's k	–
[56]	17 ETFs	2000–2016	Price data, technical indicators	CNN	Accuracy, MSE, Profit, AUROC	Keras, Tensorflow
[57]	Stocks in Dow30 and 9 Top Volume ETFs	1997–2017	Price data, technical indicators	CNN with feature imaging	Recall, precision, F1-score, annualized return	Python, Keras, Tensorflow, Java
[58]	FTSE100	2000–2017	Price data	CAE	TR, SR, MDD, mean return	–
[59]	Nasdaq Nordic (Kesko Oyj, Outokumpu Oyj, Sampo, Rautaruukki, Wartsila Oyj)	2010	Price, Volume data, 10 orders of the LOB	CNN	Precision, Recall, F1-score, Cohen's k	Theano, Scikit learn, Python
[60]	Borsa Istanbul 100 Stocks	2011–2015	75 technical indicators and OCHLV	CNN	Accuracy	Keras
[61]	ETFs and Dow30	1997–2007	Price data	CNN with feature imaging	Annualized return	Keras, Tensorflow
[62]	8 experimental assets from bond/derivative market	–	Asset prices data	RL, DMLP, Genetic Algorithm	Learning and genetic algorithm error	–
[63]	10 stocks from S&P500	–	Stock Prices	TDNN, RNN, PNN	Missed opportunities, false alarms ratio	–
[64]	London Stock Exchange	2007–2008	Limit order book state, trades, buy/sell orders, order deletions	CNN	Accuracy, kappa	Caffe
[65]	Cryptocurrencies, Bitcoin	2014–2017	Price data	CNN, RNN, LSTM	Accumulative portfolio value, MDD, SR	–

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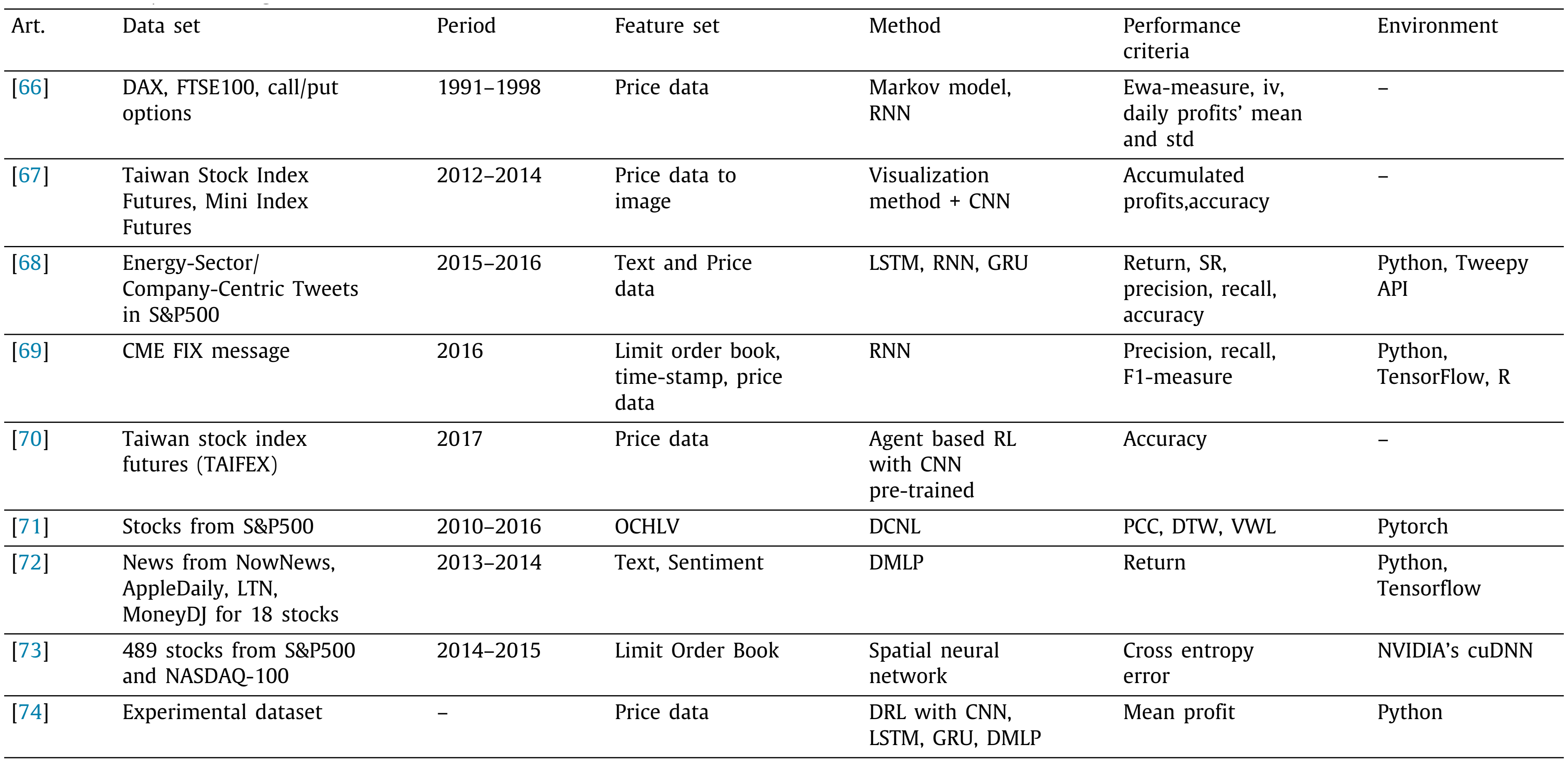
Deep learning for financial applications:

Stand-alone and/or other algorithmic models



Art.	Data set	Period	Feature set	Method	Performance criteria	Environment
[66]	DAX, FTSE100, call/put options	1991–1998	Price data	Markov model, RNN	Ewa-measure, iv, daily profits' mean and std	–
[67]	Taiwan Stock Index Futures, Mini Index Futures	2012–2014	Price data to image	Visualization method + CNN	Accumulated profits,accuracy	–
[68]	Energy-Sector/ Company-Centric Tweets in S&P500	2015–2016	Text and Price data	LSTM, RNN, GRU	Return, SR, precision, recall, accuracy	Python, Tweepy API
[69]	CME FIX message	2016	Limit order book, time-stamp, price data	RNN	Precision, recall, F1-measure	Python, TensorFlow, R
[70]	Taiwan stock index futures (TAIFEX)	2017	Price data	Agent based RL with CNN pre-trained	Accuracy	–
[71]	Stocks from S&P500	2010–2016	OCHLV	DCNL	PCC, DTW, VWL	Pytorch
[72]	News from NowNews, AppleDaily, LTN, MoneyDJ for 18 stocks	2013–2014	Text, Sentiment	DMLP	Return	Python, Tensorflow
[73]	489 stocks from S&P500 and NASDAQ-100	2014–2015	Limit Order Book	Spatial neural network	Cross entropy error	NVIDIA's cuDNN
[74]	Experimental dataset	–	Price data	DRL with CNN, LSTM, GRU, DMLP	Mean profit	Python

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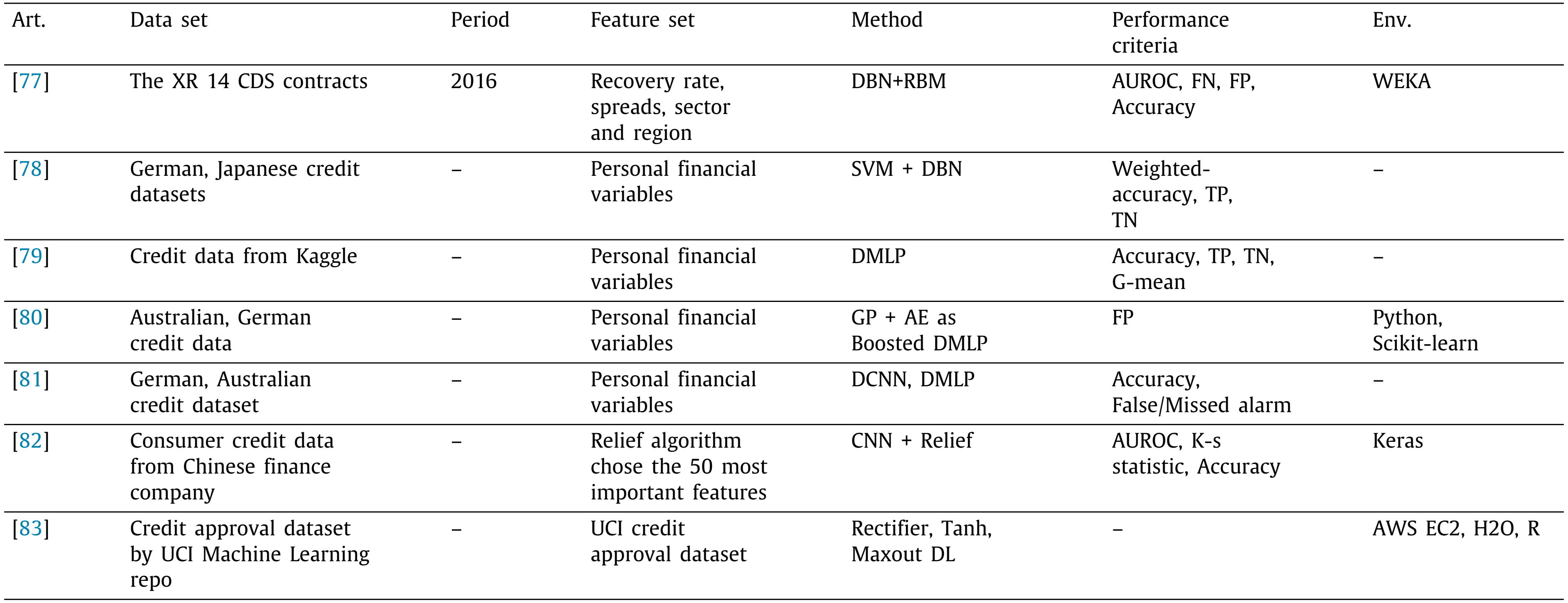
Deep learning for financial applications:

Credit scoring or classification studies



Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[77]	The XR 14 CDS contracts	2016	Recovery rate, spreads, sector and region	DBN+RBM	AUROC, FN, FP, Accuracy	WEKA
[78]	German, Japanese credit datasets	–	Personal financial variables	SVM + DBN	Weighted-accuracy, TP, TN	–
[79]	Credit data from Kaggle	–	Personal financial variables	DMLP	Accuracy, TP, TN, G-mean	–
[80]	Australian, German credit data	–	Personal financial variables	GP + AE as Boosted DMLP	FP	Python, Scikit-learn
[81]	German, Australian credit dataset	–	Personal financial variables	DCNN, DMLP	Accuracy, False/Missed alarm	–
[82]	Consumer credit data from Chinese finance company	–	Relief algorithm chose the 50 most important features	CNN + Relief	AUROC, K-s statistic, Accuracy	Keras
[83]	Credit approval dataset by UCI Machine Learning repo	–	UCI credit approval dataset	Rectifier, Tanh, Maxout DL	–	AWS EC2, H2O, R

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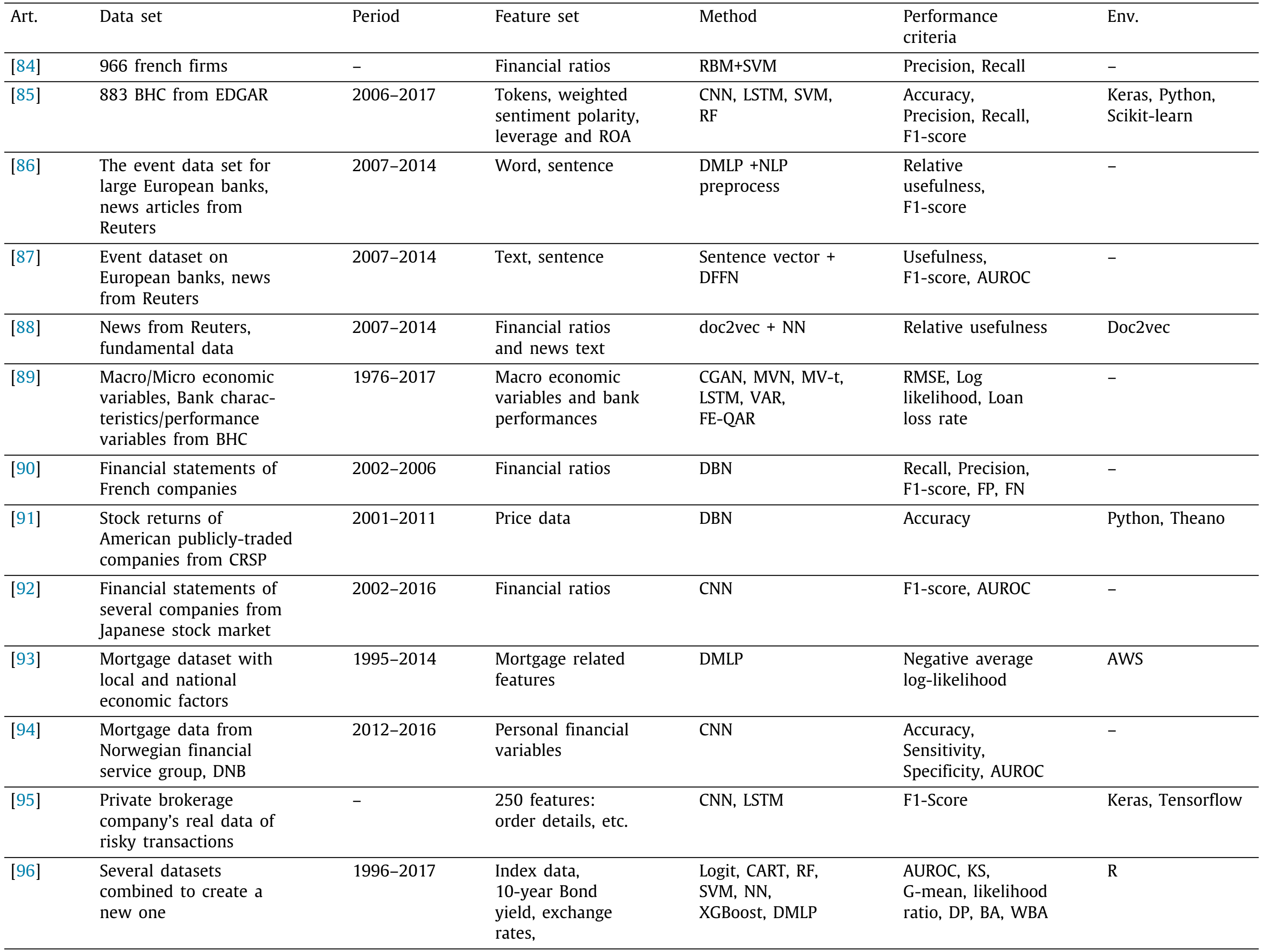
Deep learning for financial applications:

Financial distress, bankruptcy, bank risk, mortgage risk, crisis forecasting studies.



Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[84]	966 french firms	–	Financial ratios	RBM+SVM	Precision, Recall	–
[85]	883 BHC from EDGAR	2006–2017	Tokens, weighted sentiment polarity, leverage and ROA	CNN, LSTM, SVM, RF	Accuracy, Precision, Recall, F1-score	Keras, Python, Scikit-learn
[86]	The event data set for large European banks, news articles from Reuters	2007–2014	Word, sentence	DMLP +NLP preprocess	Relative usefulness, F1-score	–
[87]	Event dataset on European banks, news from Reuters	2007–2014	Text, sentence	Sentence vector + DFFN	Usefulness, F1-score, AUROC	–
[88]	News from Reuters, fundamental data	2007–2014	Financial ratios and news text	doc2vec + NN	Relative usefulness	Doc2vec
[89]	Macro/Micro economic variables, Bank characteristics/performance variables from BHC	1976–2017	Macro economic variables and bank performances	CGAN, MVN, MV-t, LSTM, VAR, FE-QAR	RMSE, Log likelihood, Loan loss rate	–
[90]	Financial statements of French companies	2002–2006	Financial ratios	DBN	Recall, Precision, F1-score, FP, FN	–
[91]	Stock returns of American publicly-traded companies from CRSP	2001–2011	Price data	DBN	Accuracy	Python, Theano
[92]	Financial statements of several companies from Japanese stock market	2002–2016	Financial ratios	CNN	F1-score, AUROC	–
[93]	Mortgage dataset with local and national economic factors	1995–2014	Mortgage related features	DMLP	Negative average log-likelihood	AWS
[94]	Mortgage data from Norwegian financial service group, DNB	2012–2016	Personal financial variables	CNN	Accuracy, Sensitivity, Specificity, AUROC	–
[95]	Private brokerage company's real data of risky transactions	–	250 features: order details, etc.	CNN, LSTM	F1-Score	Keras, Tensorflow
[96]	Several datasets combined to create a new one	1996–2017	Index data, 10-year Bond yield, exchange rates,	Logit, CART, RF, SVM, NN, XGBoost, DMLP	AUROC, KS, G-mean, likelihood ratio, DP, BA, WBA	R

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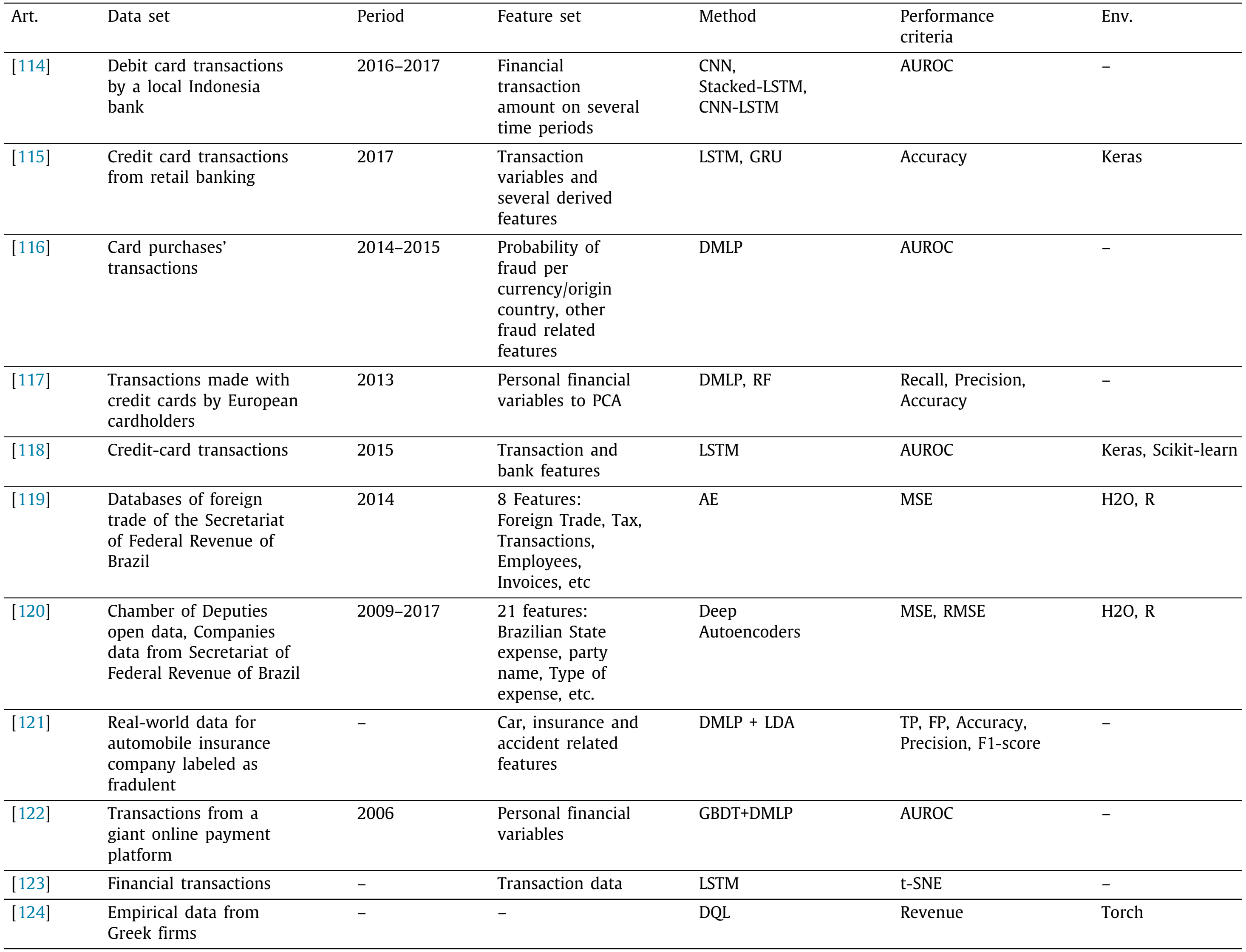
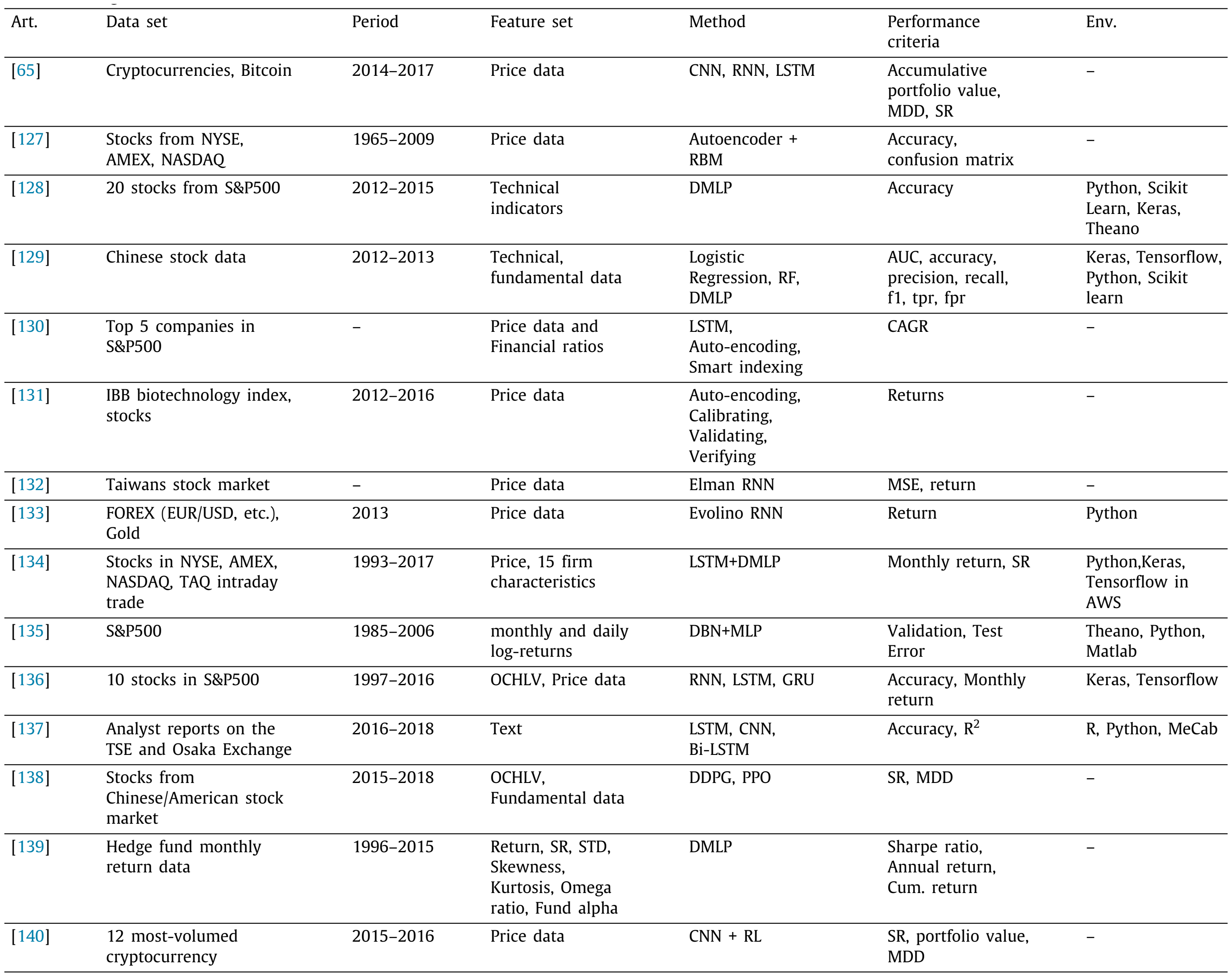
Deep learning for financial applications: Fraud detection studies



Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[114]	Debit card transactions by a local Indonesia bank	2016–2017	Financial transaction amount on several time periods	CNN, Stacked-LSTM, CNN-LSTM	AUROC	–
[115]	Credit card transactions from retail banking	2017	Transaction variables and several derived features	LSTM, GRU	Accuracy	Keras
[116]	Card purchases' transactions	2014–2015	Probability of fraud per currency/origin country, other fraud related features	DMLP	AUROC	–
[117]	Transactions made with credit cards by European cardholders	2013	Personal financial variables to PCA	DMLP, RF	Recall, Precision, Accuracy	–
[118]	Credit-card transactions	2015	Transaction and bank features	LSTM	AUROC	Keras, Scikit-learn
[119]	Databases of foreign trade of the Secretariat of Federal Revenue of Brazil	2014	8 Features: Foreign Trade, Tax, Transactions, Employees, Invoices, etc	AE	MSE	H2O, R
[120]	Chamber of Deputies open data, Companies data from Secretariat of Federal Revenue of Brazil	2009–2017	21 features: Brazilian State expense, party name, Type of expense, etc.	Deep Autoencoders	MSE, RMSE	H2O, R
[121]	Real-world data for automobile insurance company labeled as fradulent	–	Car, insurance and accident related features	DMLP + LDA	TP, FP, Accuracy, Precision, F1-score	–
[122]	Transactions from a giant online payment platform	2006	Personal financial variables	GBDT+DMLP	AUROC	–
[123]	Financial transactions	–	Transaction data	LSTM	t-SNE	–
[124]	Empirical data from Greek firms	–	–	DQL	Revenue	Torch

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications: Portfolio management studies



Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[65]	Cryptocurrencies, Bitcoin	2014–2017	Price data	CNN, RNN, LSTM	Accumulative portfolio value, MDD, SR	–
[127]	Stocks from NYSE, AMEX, NASDAQ	1965–2009	Price data	Autoencoder + RBM	Accuracy, confusion matrix	–
[128]	20 stocks from S&P500	2012–2015	Technical indicators	DMLP	Accuracy	Python, Scikit Learn, Keras, Theano
[129]	Chinese stock data	2012–2013	Technical, fundamental data	Logistic Regression, RF, DMLP	AUC, accuracy, precision, recall, f1, tpr, fpr	Keras, Tensorflow, Python, Scikit learn
[130]	Top 5 companies in S&P500	–	Price data and Financial ratios	LSTM, Auto-encoding, Smart indexing	CAGR	–
[131]	IBB biotechnology index, stocks	2012–2016	Price data	Auto-encoding, Calibrating, Validating, Verifying	Returns	–
[132]	Taiwans stock market	–	Price data	Elman RNN	MSE, return	–
[133]	FOREX (EUR/USD, etc.), Gold	2013	Price data	Evolino RNN	Return	Python
[134]	Stocks in NYSE, AMEX, NASDAQ, TAQ intraday trade	1993–2017	Price, 15 firm characteristics	LSTM+DMLP	Monthly return, SR	Python,Keras, Tensorflow in AWS
[135]	S&P500	1985–2006	monthly and daily log-returns	DBN+MLP	Validation, Test Error	Theano, Python, Matlab
[136]	10 stocks in S&P500	1997–2016	OCHLV, Price data	RNN, LSTM, GRU	Accuracy, Monthly return	Keras, Tensorflow
[137]	Analyst reports on the TSE and Osaka Exchange	2016–2018	Text	LSTM, CNN, Bi-LSTM	Accuracy, R^2	R, Python, MeCab
[138]	Stocks from Chinese/American stock market	2015–2018	OCHLV, Fundamental data	DDPG, PPO	SR, MDD	–
[139]	Hedge fund monthly return data	1996–2015	Return, SR, STD, Skewness, Kurtosis, Omega ratio, Fund alpha	DMLP	Sharpe ratio, Annual return, Cum. return	–
[140]	12 most-volumed cryptocurrency	2015–2016	Price data	CNN + RL	SR, portfolio value, MDD	–

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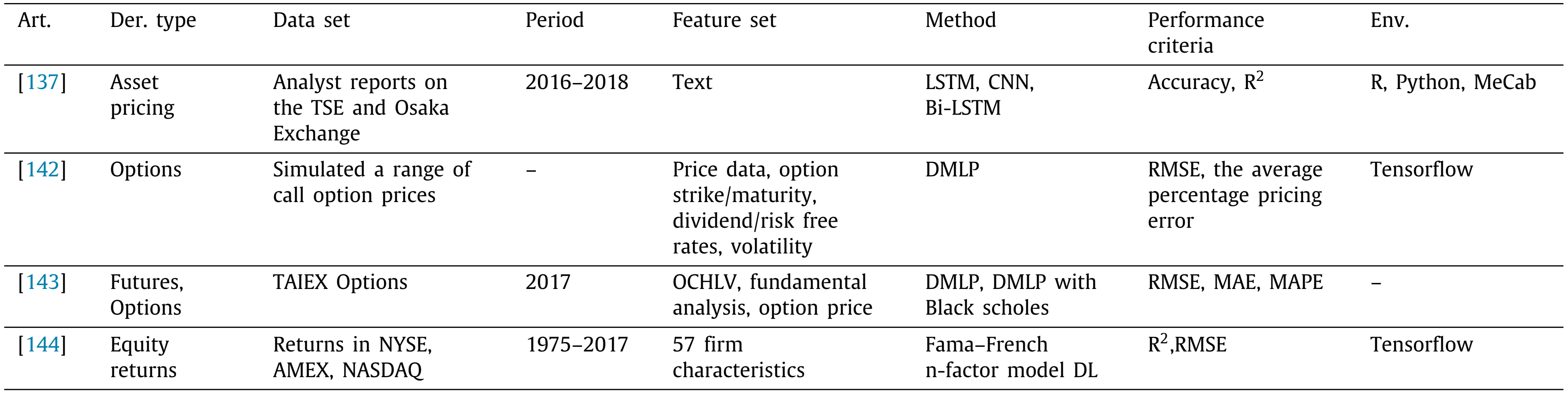
Deep learning for financial applications:

Asset pricing and derivatives market studies



Art.	Der. type	Data set	Period	Feature set	Method	Performance criteria	Env.
[137]	Asset pricing	Analyst reports on the TSE and Osaka Exchange	2016–2018	Text	LSTM, CNN, Bi-LSTM	Accuracy, R^2	R, Python, MeCab
[142]	Options	Simulated a range of call option prices	–	Price data, option strike/maturity, dividend/risk free rates, volatility	DMLP	RMSE, the average percentage pricing error	Tensorflow
[143]	Futures, Options	TAIEX Options	2017	OCHLV, fundamental analysis, option price	DMLP, DMLP with Black scholes	RMSE, MAE, MAPE	–
[144]	Equity returns	Returns in NYSE, AMEX, NASDAQ	1975–2017	57 firm characteristics	Fama–French n-factor model DL	R^2,RMSE	Tensorflow

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Deep learning for financial applications:

Cryptocurrency and blockchain studies

Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[46]	Bitcoin, Dash, Ripple, Monero, Litecoin, Dogecoin, Nxt, Namecoin	2014–2017	MA, BOLL, the CRIX daily returns, Euribor interest rates, OCHLV of EURO/UK, EURO/USD, US/JPY	LSTM, RNN, DMLP	Accuracy, F1-measure	Python, Tensorflow
[65]	Cryptocurrencies, Bitcoin	2014–2017	Price data	CNN	Accumulative portfolio value, MDD, SR	–
[140]	12 most-volumed cryptocurrency	2015–2016	Price data	CNN + RL	SR, portfolio value, MDD	
[145]	Bitcoin data	2010–2017	Hash value, bitcoin address, public/private key, digital signature, etc.	Takagi–Sugeno Fuzzy cognitive maps	Analytical hierarchy process	–
[146]	Bitcoin data	2012, 2013, 2016	TransactionId, input/output Addresses, timestamp	Graph embedding using heuristic, laplacian eigen-map, deep AE	F1-score	–
[147]	Bitcoin, Litecoin, StockTwits	2015–2018	OCHLV, technical indicators, sentiment analysis	CNN, LSTM, State Frequency Model	MSE	Keras, Tensorflow
[148]	Bitcoin	2013–2016	Price data	Bayesian optimized RNN, LSTM	Sensitivity, specificity, precision, accuracy, RMSE	Keras, Python, Hyperas

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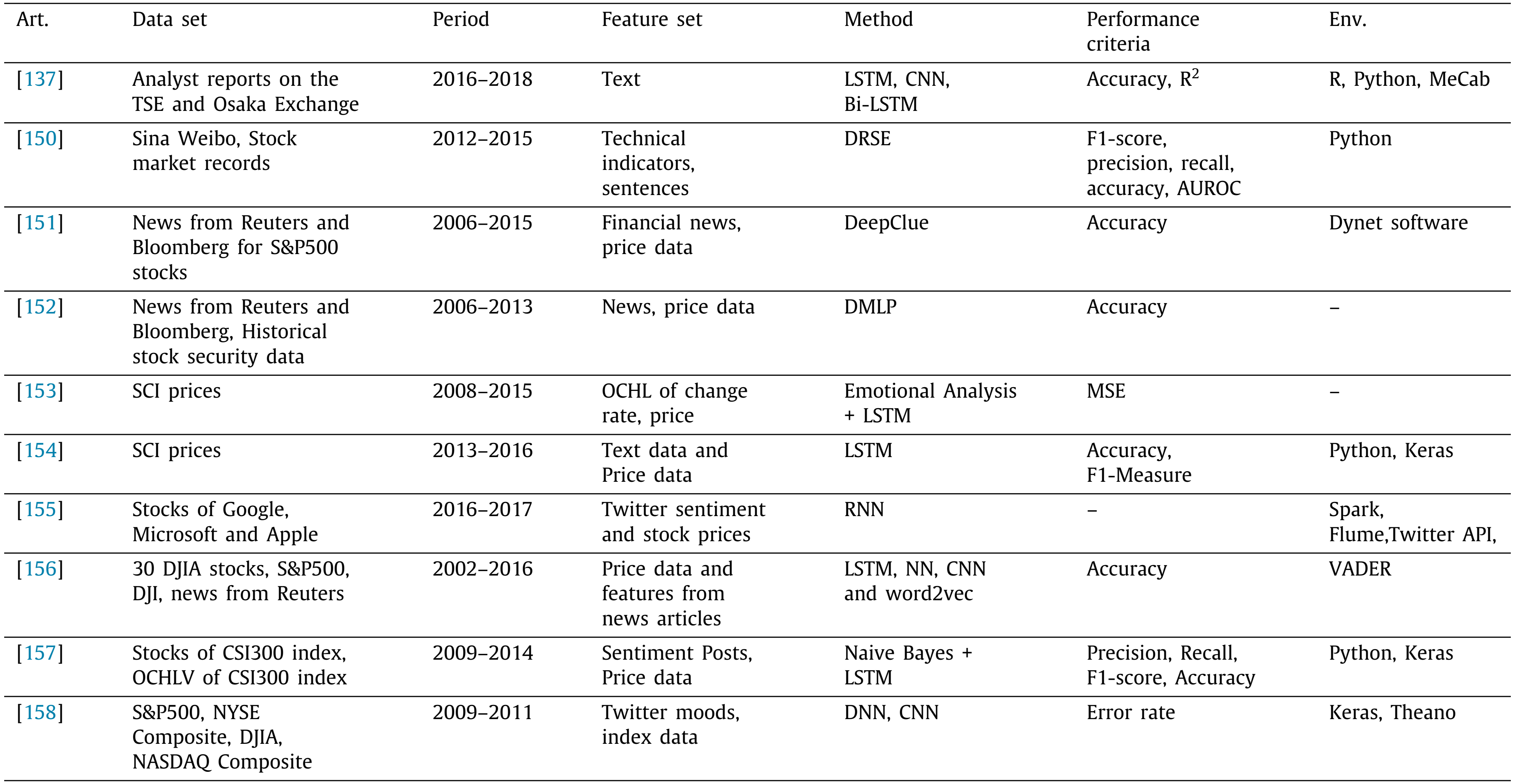
Deep learning for financial applications:

Financial sentiment studies coupled with text mining for forecasting



Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[137]	Analyst reports on the TSE and Osaka Exchange	2016–2018	Text	LSTM, CNN, Bi-LSTM	Accuracy, R^2	R, Python, MeCab
[150]	Sina Weibo, Stock market records	2012–2015	Technical indicators, sentences	DRSE	F1-score, precision, recall, accuracy, AUROC	Python
[151]	News from Reuters and Bloomberg for S&P500 stocks	2006–2015	Financial news, price data	DeepClue	Accuracy	Dynet software
[152]	News from Reuters and Bloomberg, Historical stock security data	2006–2013	News, price data	DMLP	Accuracy	–
[153]	SCI prices	2008–2015	OCHL of change rate, price	Emotional Analysis + LSTM	MSE	–
[154]	SCI prices	2013–2016	Text data and Price data	LSTM	Accuracy, F1-Measure	Python, Keras
[155]	Stocks of Google, Microsoft and Apple	2016–2017	Twitter sentiment and stock prices	RNN	–	Spark, Flume,Twitter API,
[156]	30 DJIA stocks, S&P500, DJI, news from Reuters	2002–2016	Price data and features from news articles	LSTM, NN, CNN and word2vec	Accuracy	VADER
[157]	Stocks of CSI300 index, OCHLV of CSI300 index	2009–2014	Sentiment Posts, Price data	Naive Bayes + LSTM	Precision, Recall, F1-score, Accuracy	Python, Keras
[158]	S&P500, NYSE Composite, DJIA, NASDAQ Composite	2009–2011	Twitter moods, index data	DNN, CNN	Error rate	Keras, Theano

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:

Text mining studies without sentiment analysis for forecasting

Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[68]	Energy-Sector/ Company-Centric Tweets in S&P500	2015–2016	Text and Price data	RNN, KNN, SVR, LinR	Return, SR, precision, recall, accuracy	Python, Tweepy API
[165]	News from Reuters, Bloomberg	2006–2013	Financial news, price data	Bi-GRU	Accuracy	Python, Keras
[166]	News from Sina.com, ACE2005 Chinese corpus	2012–2016	A set of news text	Their unique algorithm	Precision, Recall, F1-score	–
[167]	CDAX stock market data	2010–2013	Financial news, stock market data	LSTM	MSE, RMSE, MAE, Accuracy, AUC	TensorFlow, Theano, Python, Scikit-Learn
[168]	Apple, Airbus, Amazon news from Reuters, Bloomberg, S&P500 stock prices	2006–2013	Price data, news, technical indicators	TGRU, stock2vec	Accuracy, precision, AUROC	Keras, Python
[169]	S&P500 Index, 15 stocks in S&P500	2006–2013	News from Reuters and Bloomberg	CNN	Accuracy, MCC	–
[170]	S&P500 index news from Reuters	2006–2013	Financial news titles, Technical indicators	SI-RCNN (LSTM + CNN)	Accuracy	–
[171]	10 stocks in Nikkei 225 and news	2001–2008	Textual information and Stock prices	Paragraph Vector + LSTM	Profit	–
[172]	NIFTY50 Index, NIFTY Bank/Auto/IT/Energy Index, News	2013–2017	Index data, news	LSTM	MCC, Accuracy	–
[173]	Price data, index data, news, social media data	2015	Price data, news from articles and social media	Coupled matrix and tensor	Accuracy, MCC	Jieba
[174]	HS300	2015–2017	Social media news, price data	RNN-Boost with LDA	Accuracy, MAE, MAPE, RMSE	Python, Scikit-learn

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:

Text mining studies without sentiment analysis for forecasting

Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[175]	News and Chinese stock data	2014–2017	Selected words in a news	HAN	Accuracy, Annual return	–
[176]	News, stock prices from Hong Kong Stock Exchange	2001	Price data and TF-IDF from news	ELM, DLR, PCA, BELM, KELM, NN	Accuracy	Matlab
[177]	TWSE index, 4 stocks in TWSE	2001–2017	Technical indicators, Price data, News	CNN + LSTM	RMSE, Profit	Keras, Python, TALIB
[178]	Stock of Tsugami Corporation	2013	Price data	LSTM	RMSE	Keras, Tensorflow
[179]	News, Nikkei Stock Average and 10-Nikkei companies	1999–2008	news, MACD	RNN, RBM+DBN	Accuracy, *P*-value	–
[180]	ISMIS 2017 Data Mining Competition dataset	–	Expert identifier, classes	LSTM + GRU + FFNN	Accuracy	–
[181]	Reuters, Bloomberg News, S&P500 price	2006–2013	News and sentences	LSTM	Accuracy	–
[182]	APPL from S&P500 and news from Reuters	2011–2017	Input news, OCHLV, Technical indicators	CNN + LSTM, CNN+SVM	Accuracy, F1-score	Tensorflow
[183]	Nikkei225, S&P500, news from Reuters and Bloomberg	2001–2013	Stock price data and news	DGM	Accuracy, MCC, %profit	–
[184]	Stocks from S&P500	2006–2013	Text (news) and Price data	LAR+News, RF+News	MAPE, RMSE	–

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:

Financial sentiment studies coupled with text mining without forecasting

Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[85]	883 BHC from EDGAR	2006–2017	Tokens, weighted sentiment polarity, leverage and ROA	CNN, LSTM, SVM, Random Forest	Accuracy, Precision, Recall, F1-score	Keras, Python, Scikit-learn
[185]	SemEval-2017 dataset, financial text, news, stock market data	2017	Sentiments in Tweets, News headlines	Ensemble SVR, CNN, LSTM, GRU	Cosine similarity score, agreement score, class score	Python, Keras, Scikit Learn
[186]	Financial news from Reuters	2006–2015	Word vector, Lexical and Contextual input	Targeted dependency tree LSTM	Cumulative abnormal return	–
[187]	Stock sentiment analysis from StockTwits	2015	StockTwits messages	LSTM, Doc2Vec, CNN	Accuracy, precision, recall, f-measure, AUC	–
[188]	Sina Weibo, Stock market records	2012–2015	Technical indicators, sentences	DRSE	F1-score, precision, recall, accuracy, AUROC	Python
[189]	News from NowNews, AppleDaily, LTN, MoneyDJ for 18 stocks	2013–2014	Text, Sentiment	LSTM, CNN	Return	Python, Tensorflow
[190]	StockTwits	2008–2016	Sentences, StockTwits messages	CNN, LSTM, GRU	MCC, WSURT	Keras, Tensorflow
[191]	Financial statements of Japan companies	–	Sentences, text	DMLP	Precision, recall, f-score	–
[192]	Twitter posts, news headlines	–	Sentences, text	Deep-FASP	Accuracy, MSE, R^2	–
[193]	Forums data	2004–2013	Sentences and keywords	Recursive neural tensor networks	Precision, recall, f-measure	–
[194]	News from Financial Times related US stocks	–	Sentiment of news headlines	SVR, Bidirectional LSTM	Cosine similarity	Python, Scikit Learn, Keras, Tensorflow

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:
Other text mining studies

Art.	Data set	Period	Feature set	Method	Performance criteria	**Env.**
[72]	News from NowNews, AppleDaily, LTN, MoneyDJ for 18 stocks	2013–2014	Text, Sentiment	DMLP	Return	Python, Tensorflow
[86]	The event data set for large European banks, news articles from Reuters	2007–2014	Word, sentence	DMLP +NLP preprocess	Relative usefulness, F1-score	–
[87]	Event dataset on European banks, news from Reuters	2007–2014	Text, sentence	Sentence vector + DFFN	Usefulness, F1-score, AUROC	–
[88]	News from Reuters, fundamental data	2007–2014	Financial ratios and news text	doc2vec + NN	Relative usefulness	Doc2vec
[121]	Real-world data for automobile insurance company labeled as fradulent	–	Car, insurance and accident related features	DMLP + LDA	TP, FP, Accuracy, Precision, F1-score	–
[123]	Financial transactions	–	Transaction data	LSTM	t-SNE	–
[195]	Taiwan's National Pension Insurance	2008–2014	Insured's id, area-code, gender, etc.	RNN	Accuracy, total error	Python
[196]	StockTwits	2015–2016	Sentences, StockTwits messages	Doc2vec, CNN	Accuracy, precision, recall, f-measure, AUC	Python, Tensorflow

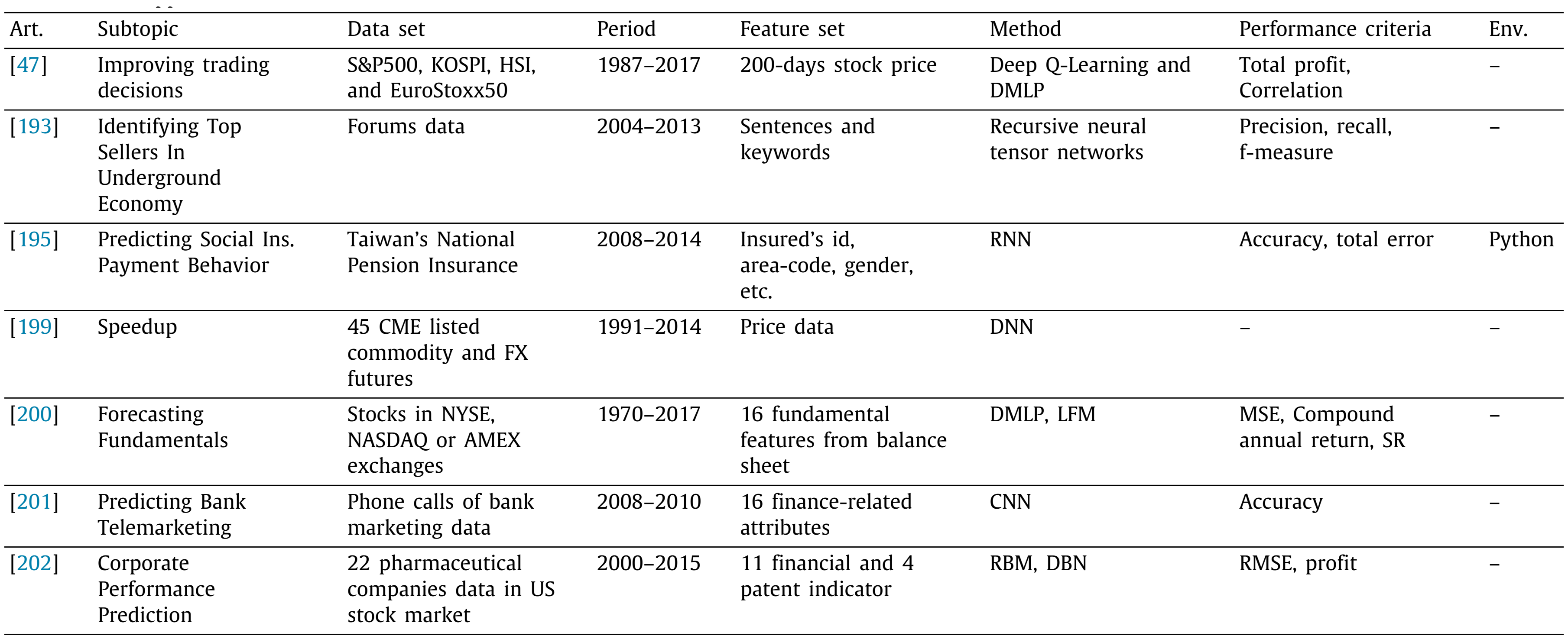
Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:
Other theoretical or conceptual studies

Art.	SubTopic	IsTimeSeries?	Data set	Period	Feature set	Method
[197]	Analysis of AE, SVD	Yes	Selected stocks from the IBB index and stock of Amgen Inc.	2012–2014	Price data	AE, SVD
[198]	Fraud Detection in Banking	No	Risk Management / Fraud Detection	–	–	DRL

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

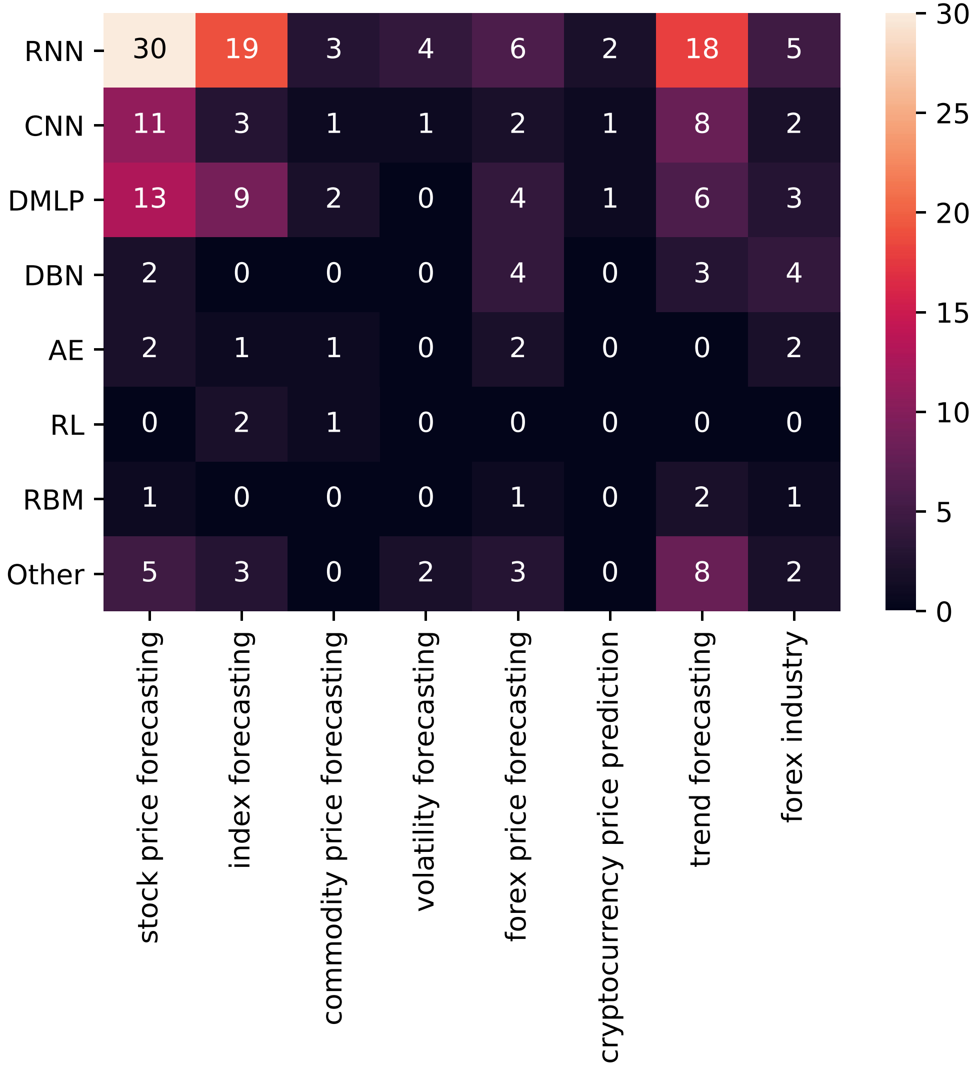
Deep learning for financial applications:
Other financial applications



Art.	Subtopic	Data set	Period	Feature set	Method	Performance criteria	Env.
[47]	Improving trading decisions	S&P500, KOSPI, HSI, and EuroStoxx50	1987–2017	200-days stock price	Deep Q-Learning and DMLP	Total profit, Correlation	–
[193]	Identifying Top Sellers In Underground Economy	Forums data	2004–2013	Sentences and keywords	Recursive neural tensor networks	Precision, recall, f-measure	–
[195]	Predicting Social Ins. Payment Behavior	Taiwan's National Pension Insurance	2008–2014	Insured's id, area-code, gender, etc.	RNN	Accuracy, total error	Python
[199]	Speedup	45 CME listed commodity and FX futures	1991–2014	Price data	DNN	–	–
[200]	Forecasting Fundamentals	Stocks in NYSE, NASDAQ or AMEX exchanges	1970–2017	16 fundamental features from balance sheet	DMLP, LFM	MSE, Compound annual return, SR	–
[201]	Predicting Bank Telemarketing	Phone calls of bank marketing data	2008–2010	16 finance-related attributes	CNN	Accuracy	–
[202]	Corporate Performance Prediction	22 pharmaceutical companies data in US stock market	2000–2015	11 financial and 4 patent indicator	RBM, DBN	RMSE, profit	–

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

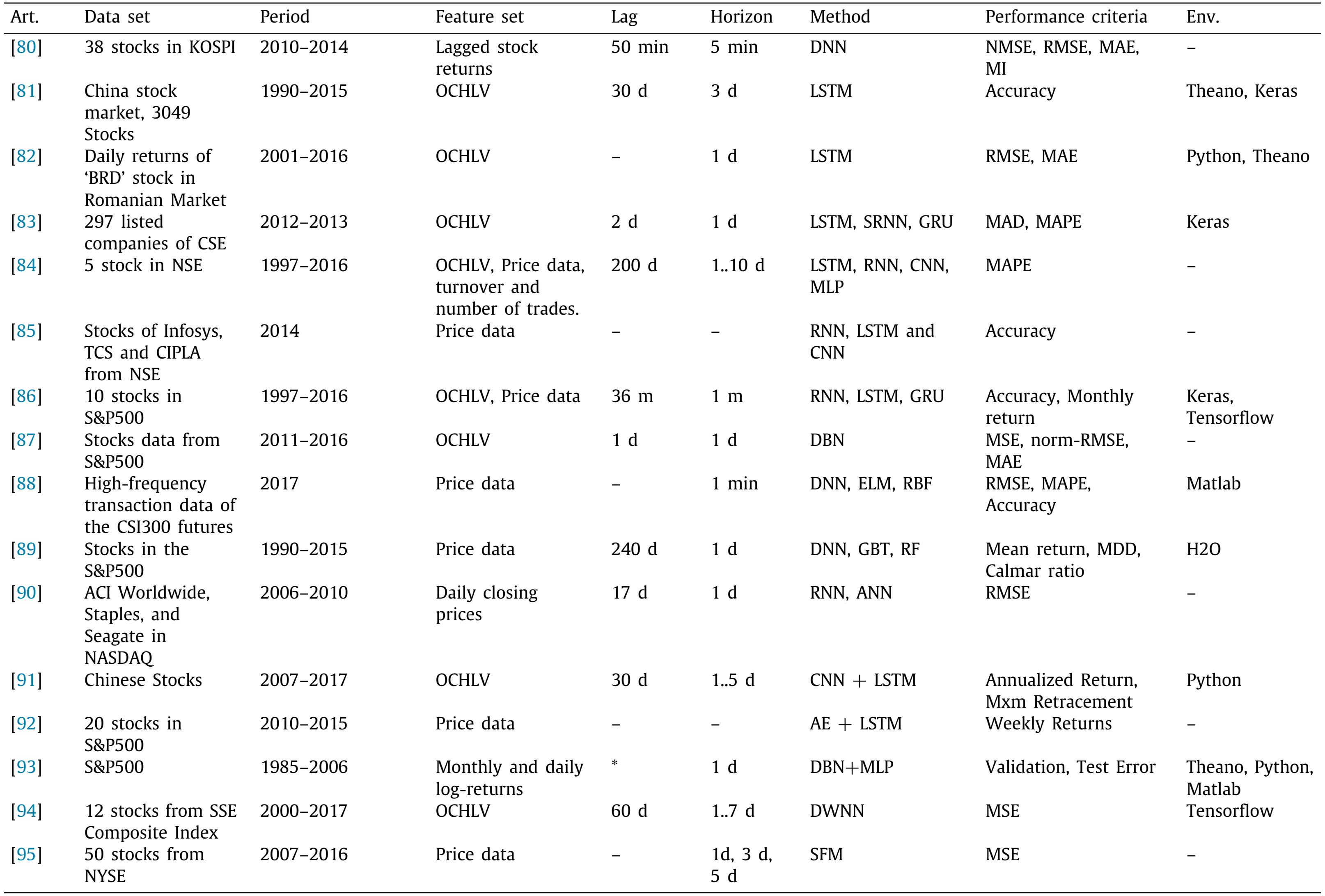
Financial time series forecasting with deep learning: Topic-model heatmap



	stock price forecasting	index forecasting	commodity price forecasting	volatility forecasting	forex price forecasting	cryptocurrency price prediction	trend forecasting	forex industry
RNN	30	19	3	4	6	2	18	5
CNN	11	3	1	1	2	1	8	2
DMLP	13	9	2	0	4	1	6	3
DBN	2	0	0	0	4	0	3	4
AE	2	1	1	0	2	0	0	2
RL	0	2	1	0	0	0	0	0
RBM	1	0	0	0	1	0	2	1
Other	5	3	0	2	3	0	8	2

Source: Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020), "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019." Applied Soft Computing 90 (2020): 106181.

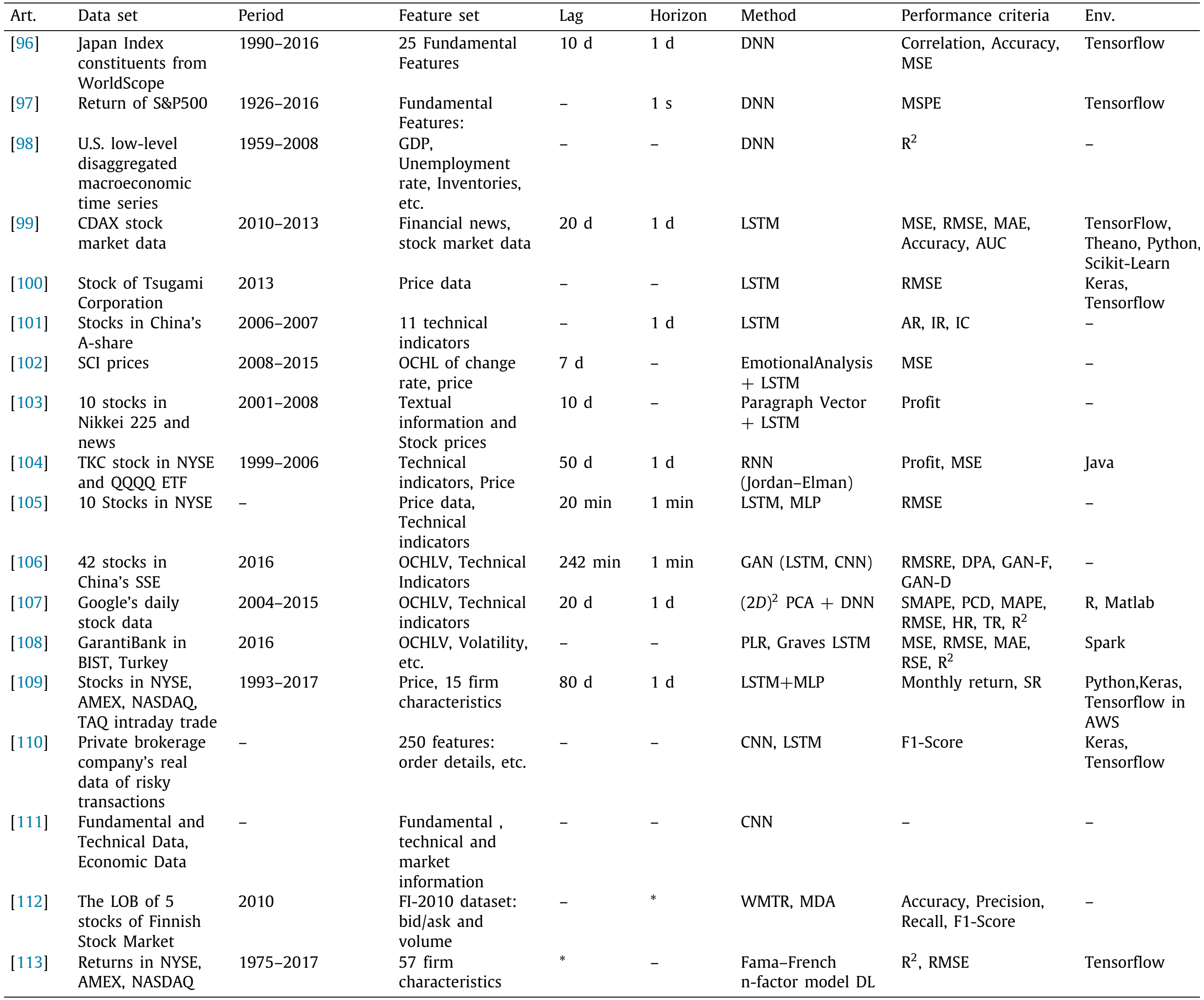
Stock price forecasting using only raw time series data



Art.	Data set	Period	Feature set	Lag	Horizon	Method	Performance criteria	Env.
[80]	38 stocks in KOSPI	2010–2014	Lagged stock returns	50 min	5 min	DNN	NMSE, RMSE, MAE, MI	–
[81]	China stock market, 3049 Stocks	1990–2015	OCHLV	30 d	3 d	LSTM	Accuracy	Theano, Keras
[82]	Daily returns of 'BRD' stock in Romanian Market	2001–2016	OCHLV	–	1 d	LSTM	RMSE, MAE	Python, Theano
[83]	297 listed companies of CSE	2012–2013	OCHLV	2 d	1 d	LSTM, SRNN, GRU	MAD, MAPE	Keras
[84]	5 stock in NSE	1997–2016	OCHLV, Price data, turnover and number of trades.	200 d	1..10 d	LSTM, RNN, CNN, MLP	MAPE	–
[85]	Stocks of Infosys, TCS and CIPLA from NSE	2014	Price data	–	–	RNN, LSTM and CNN	Accuracy	–
[86]	10 stocks in S&P500	1997–2016	OCHLV, Price data	36 m	1 m	RNN, LSTM, GRU	Accuracy, Monthly return	Keras, Tensorflow
[87]	Stocks data from S&P500	2011–2016	OCHLV	1 d	1 d	DBN	MSE, norm-RMSE, MAE	–
[88]	High-frequency transaction data of the CSI300 futures	2017	Price data	–	1 min	DNN, ELM, RBF	RMSE, MAPE, Accuracy	Matlab
[89]	Stocks in the S&P500	1990–2015	Price data	240 d	1 d	DNN, GBT, RF	Mean return, MDD, Calmar ratio	H2O
[90]	ACI Worldwide, Staples, and Seagate in NASDAQ	2006–2010	Daily closing prices	17 d	1 d	RNN, ANN	RMSE	–
[91]	Chinese Stocks	2007–2017	OCHLV	30 d	1..5 d	CNN + LSTM	Annualized Return, Mxm Retracement	Python
[92]	20 stocks in S&P500	2010–2015	Price data	–	–	AE + LSTM	Weekly Returns	–
[93]	S&P500	1985–2006	Monthly and daily log-returns	*	1 d	DBN+MLP	Validation, Test Error	Theano, Python, Matlab
[94]	12 stocks from SSE Composite Index	2000–2017	OCHLV	60 d	1..7 d	DWNN	MSE	Tensorflow
[95]	50 stocks from NYSE	2007–2016	Price data	–	1d, 3 d, 5 d	SFM	MSE	–

Source: Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020), "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019." Applied Soft Computing 90 (2020): 106181.

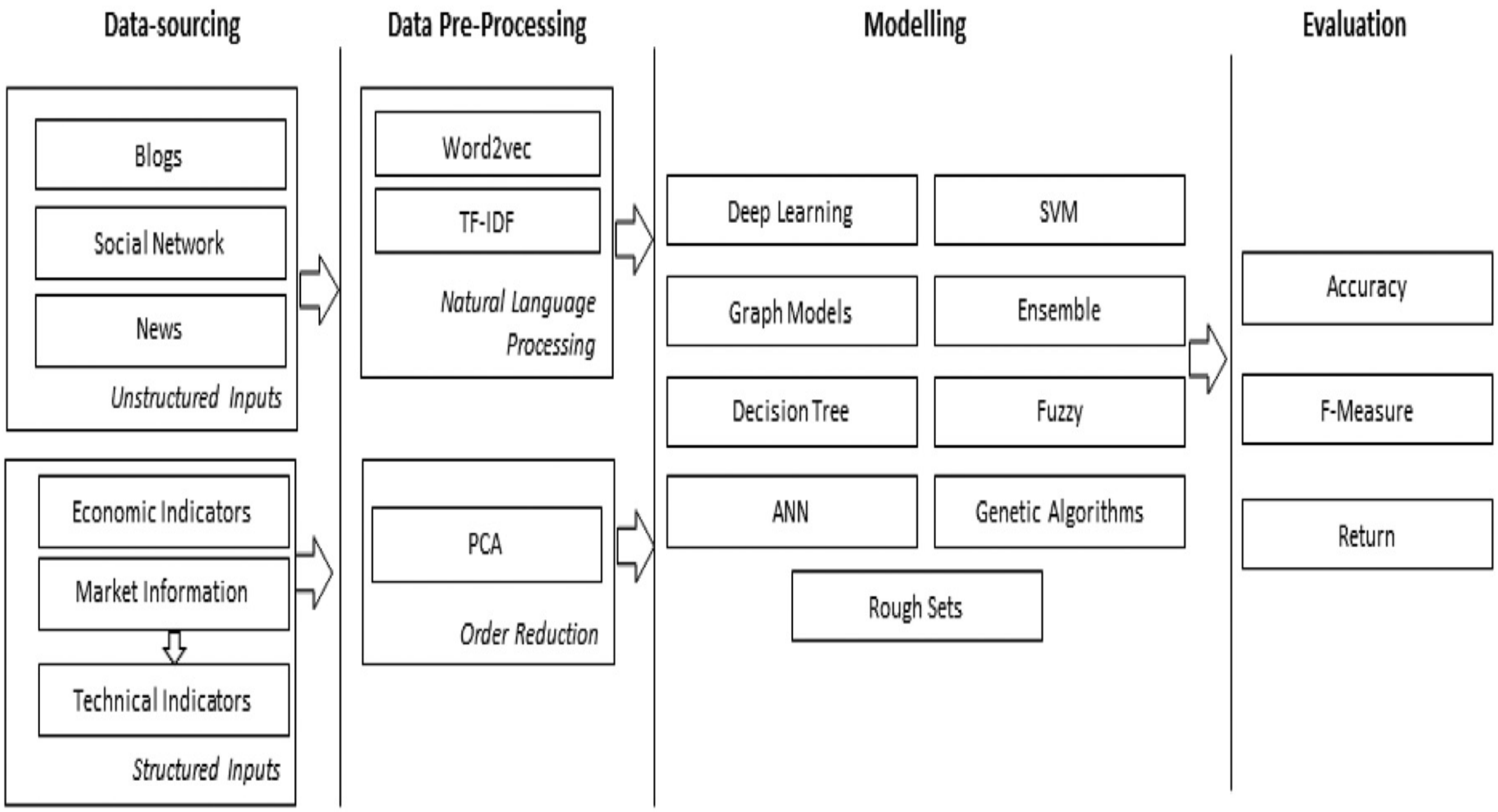
Stock price forecasting using various data



Art.	Data set	Period	Feature set	Lag	Horizon	Method	Performance criteria	Env.
[96]	Japan Index constituents from WorldScope	1990–2016	25 Fundamental Features	10 d	1 d	DNN	Correlation, Accuracy, MSE	Tensorflow
[97]	Return of S&P500	1926–2016	Fundamental Features:	–	1 s	DNN	MSPE	Tensorflow
[98]	U.S. low-level disaggregated macroeconomic time series	1959–2008	GDP, Unemployment rate, Inventories, etc.	–	–	DNN	R^2	–
[99]	CDAX stock market data	2010–2013	Financial news, stock market data	20 d	1 d	LSTM	MSE, RMSE, MAE, Accuracy, AUC	TensorFlow, Theano, Python, Scikit-Learn
[100]	Stock of Tsugami Corporation	2013	Price data	–	–	LSTM	RMSE	Keras, Tensorflow
[101]	Stocks in China's A-share	2006–2007	11 technical indicators	–	1 d	LSTM	AR, IR, IC	–
[102]	SCI prices	2008–2015	OCHL of change rate, price	7 d	–	EmotionalAnalysis + LSTM	MSE	–
[103]	10 stocks in Nikkei 225 and news	2001–2008	Textual information and Stock prices	10 d	–	Paragraph Vector + LSTM	Profit	–
[104]	TKC stock in NYSE and QQQQ ETF	1999–2006	Technical indicators, Price	50 d	1 d	RNN (Jordan–Elman)	Profit, MSE	Java
[105]	10 Stocks in NYSE	–	Price data, Technical indicators	20 min	1 min	LSTM, MLP	RMSE	–
[106]	42 stocks in China's SSE	2016	OCHLV, Technical Indicators	242 min	1 min	GAN (LSTM, CNN)	RMSRE, DPA, GAN-F, GAN-D	–
[107]	Google's daily stock data	2004–2015	OCHLV, Technical indicators	20 d	1 d	$(2D)^2$ PCA + DNN	SMAPE, PCD, MAPE, RMSE, HR, TR, R^2	R, Matlab
[108]	GarantiBank in BIST, Turkey	2016	OCHLV, Volatility, etc.	–	–	PLR, Graves LSTM	MSE, RMSE, MAE, RSE, R^2	Spark
[109]	Stocks in NYSE, AMEX, NASDAQ, TAQ intraday trade	1993–2017	Price, 15 firm characteristics	80 d	1 d	LSTM+MLP	Monthly return, SR	Python,Keras, Tensorflow in AWS
[110]	Private brokerage company's real data of risky transactions	–	250 features: order details, etc.	–	–	CNN, LSTM	F1-Score	Keras, Tensorflow
[111]	Fundamental and Technical Data, Economic Data	–	Fundamental , technical and market information	–	–	CNN	–	–
[112]	The LOB of 5 stocks of Finnish Stock Market	2010	FI-2010 dataset: bid/ask and volume	–	*	WMTR, MDA	Accuracy, Precision, Recall, F1-Score	–
[113]	Returns in NYSE, AMEX, NASDAQ	1975–2017	57 firm characteristics	*	–	Fama–French n-factor model DL	R^2, RMSE	Tensorflow

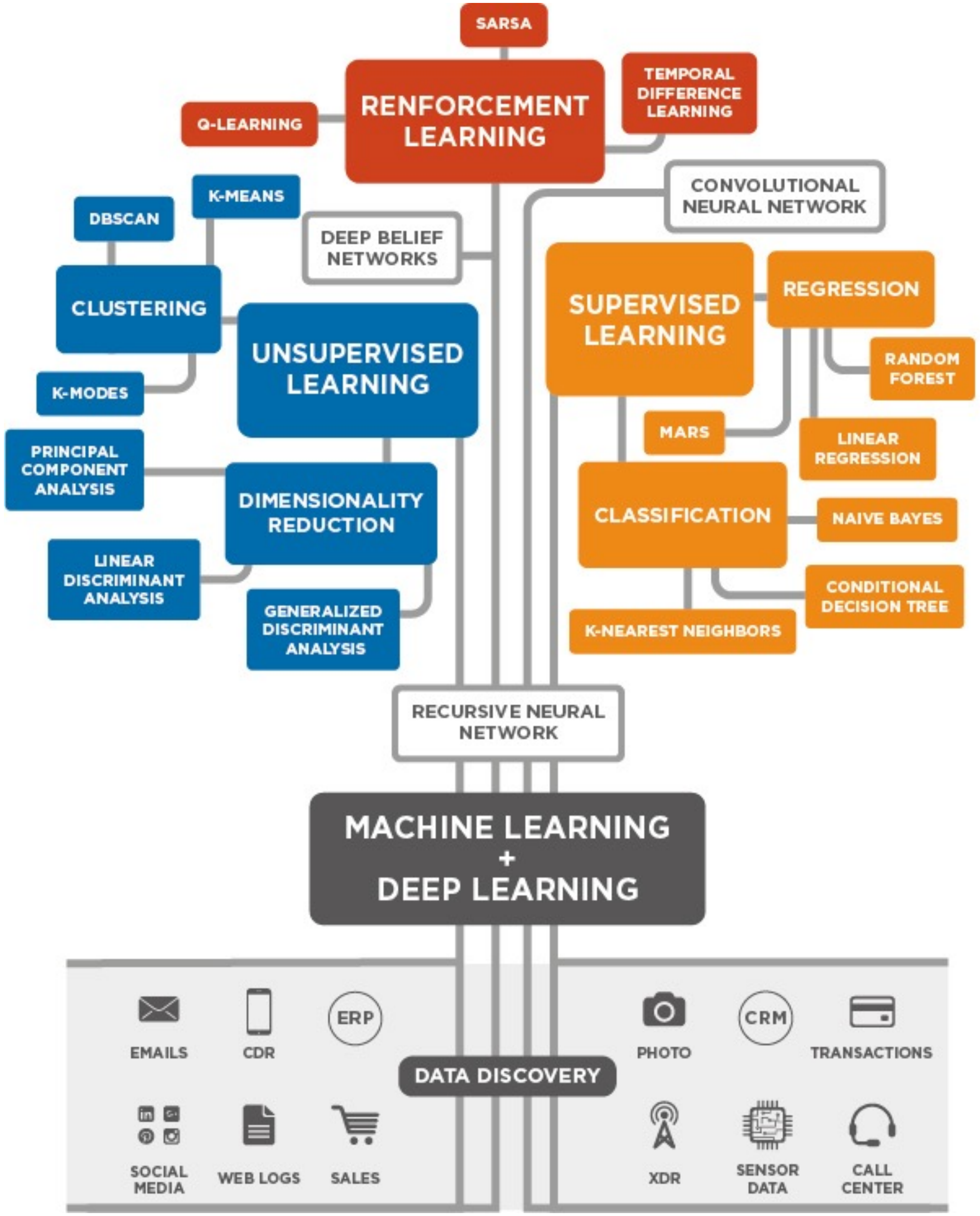
Source: Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020), "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019." Applied Soft Computing 90 (2020): 106181.

Stock Market Movement Forecast:
Phases of the stock market modeling



Source: O. Bustos and A. Pomares-Quimbaya (2020), "Stock Market Movement Forecast: A Systematic Review." Expert Systems with Applications (2020): 113464.

3 Machine Learning Algorithms



SARSA

Q-LEARNING

RENFORCEMENT LEARNING

TEMPORAL DIFFERENCE LEARNING

DBSCAN

K-MEANS

DEEP BELIEF NETWORKS

CONVOLUTIONAL NEURAL NETWORK

CLUSTERING

UNSUPERVISED LEARNING

SUPERVISED LEARNING

REGRESSION

RANDOM FOREST

K-MODES

MARS

LINEAR REGRESSION

PRINCIPAL COMPONENT ANALYSIS

DIMENSIONALITY REDUCTION

CLASSIFICATION

NAIVE BAYES

LINEAR DISCRIMINANT ANALYSIS

CONDITIONAL DECISION TREE

GENERALIZED DISCRIMINANT ANALYSIS

K-NEAREST NEIGHBORS

RECURSIVE NEURAL NETWORK

MACHINE LEARNING
+
DEEP LEARNING

EMAILS

CDR

ERP

PHOTO

CRM

TRANSACTIONS

DATA DISCOVERY

SOCIAL MEDIA

WEB LOGS

SALES

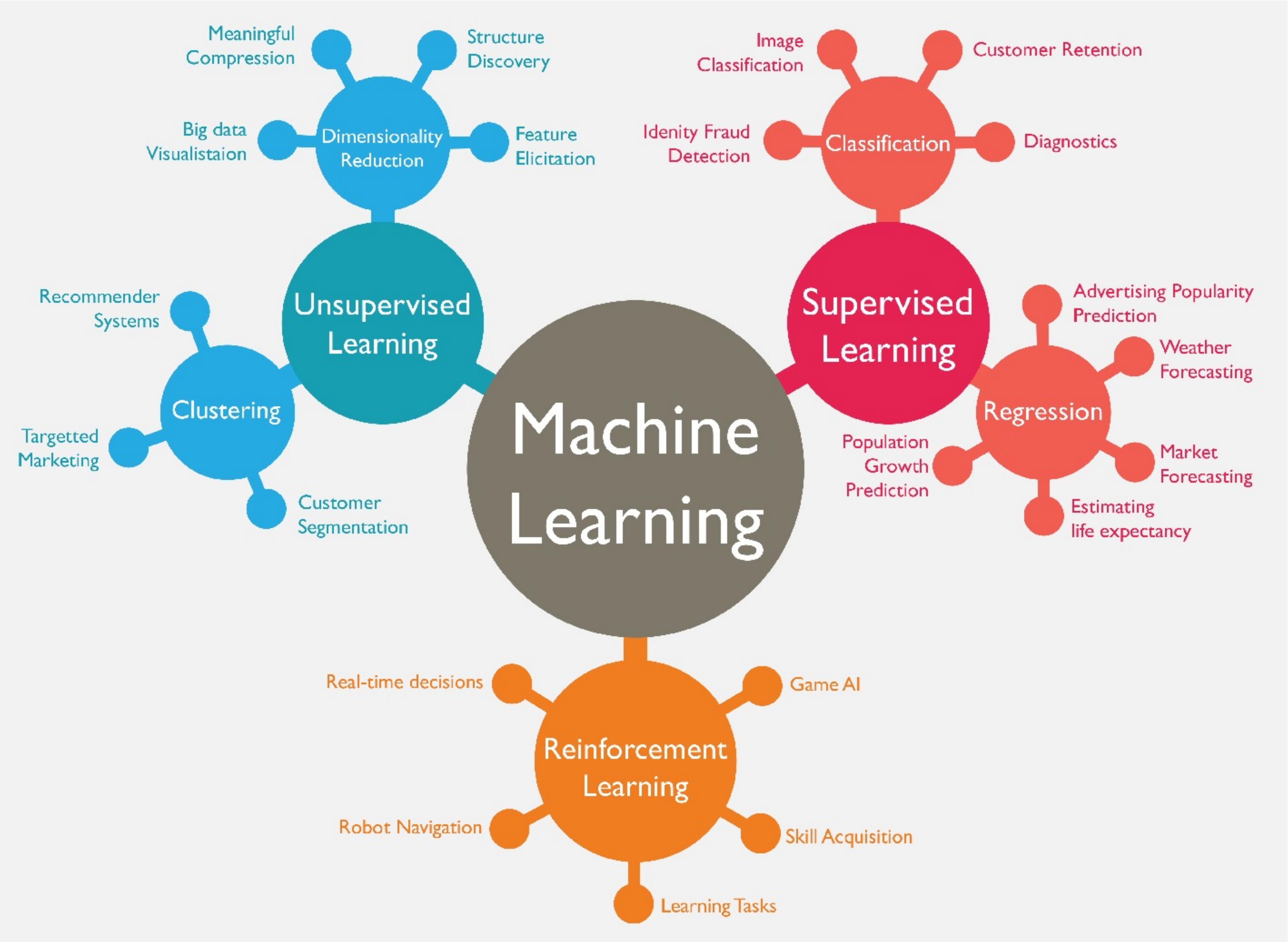
XDR

SENSOR DATA

CALL CENTER

Source: Enrico Galimberti, http://blogs.teradata.com/data-points/tree-machine-learning-algorithms/

Machine Learning (ML)



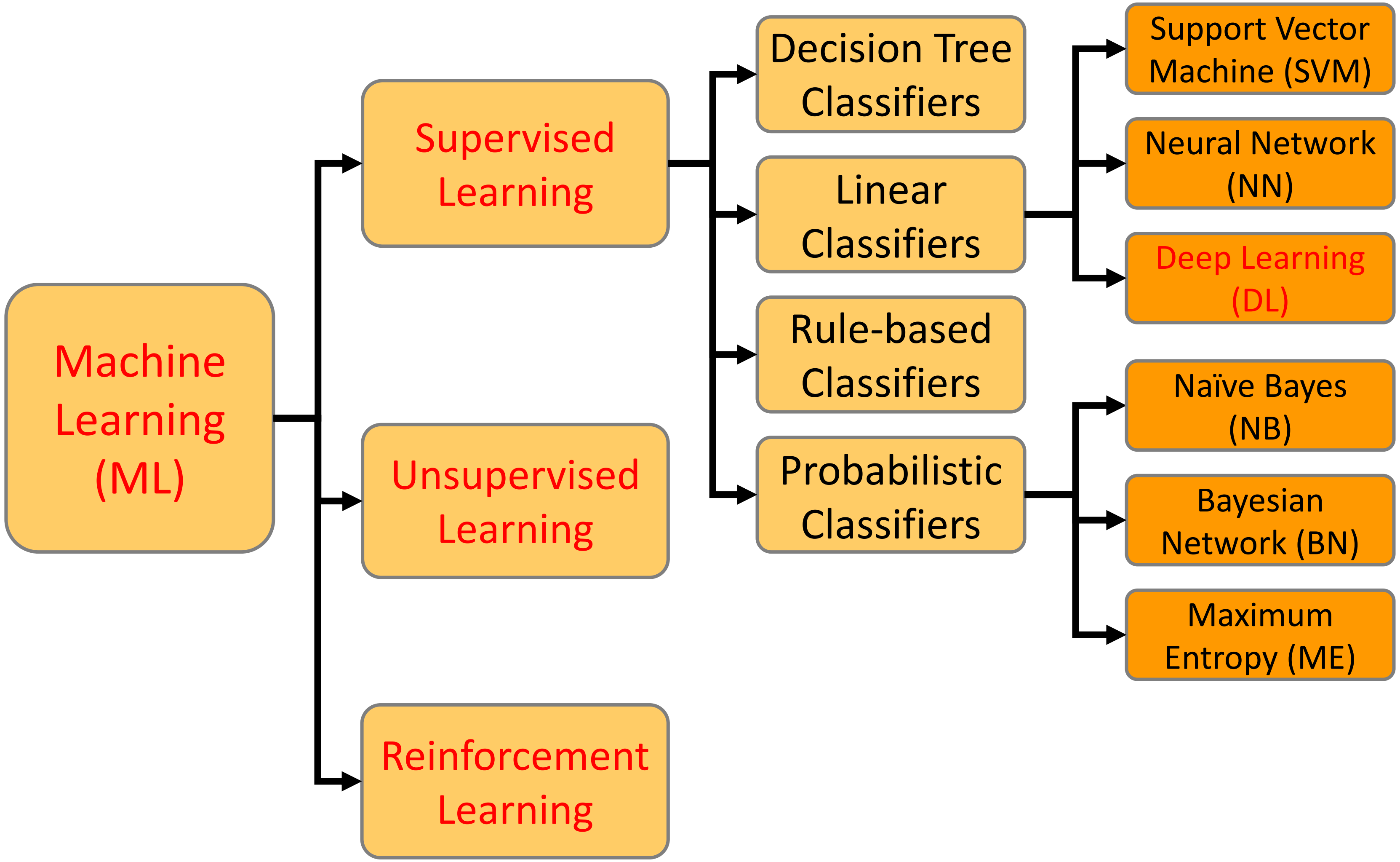
Source: https://www.mactores.com/services/aws-big-data-machine-learning-cognitive-services/

Machine Learning Models

- Deep Learning
- Association rules
- Decision tree
- Clustering
- Bayesian
- Kernel
- Ensemble
- Dimensionality reduction
- Regression Analysis
- Instance based

Source: Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing

Machine Learning (ML) / Deep Learning (DL)



Machine Learning (ML)

Supervised Learning

Decision Tree Classifiers

Linear Classifiers

Support Vector Machine (SVM)

Neural Network (NN)

Deep Learning (DL)

Rule-based Classifiers

Probabilistic Classifiers

Naïve Bayes (NB)

Bayesian Network (BN)

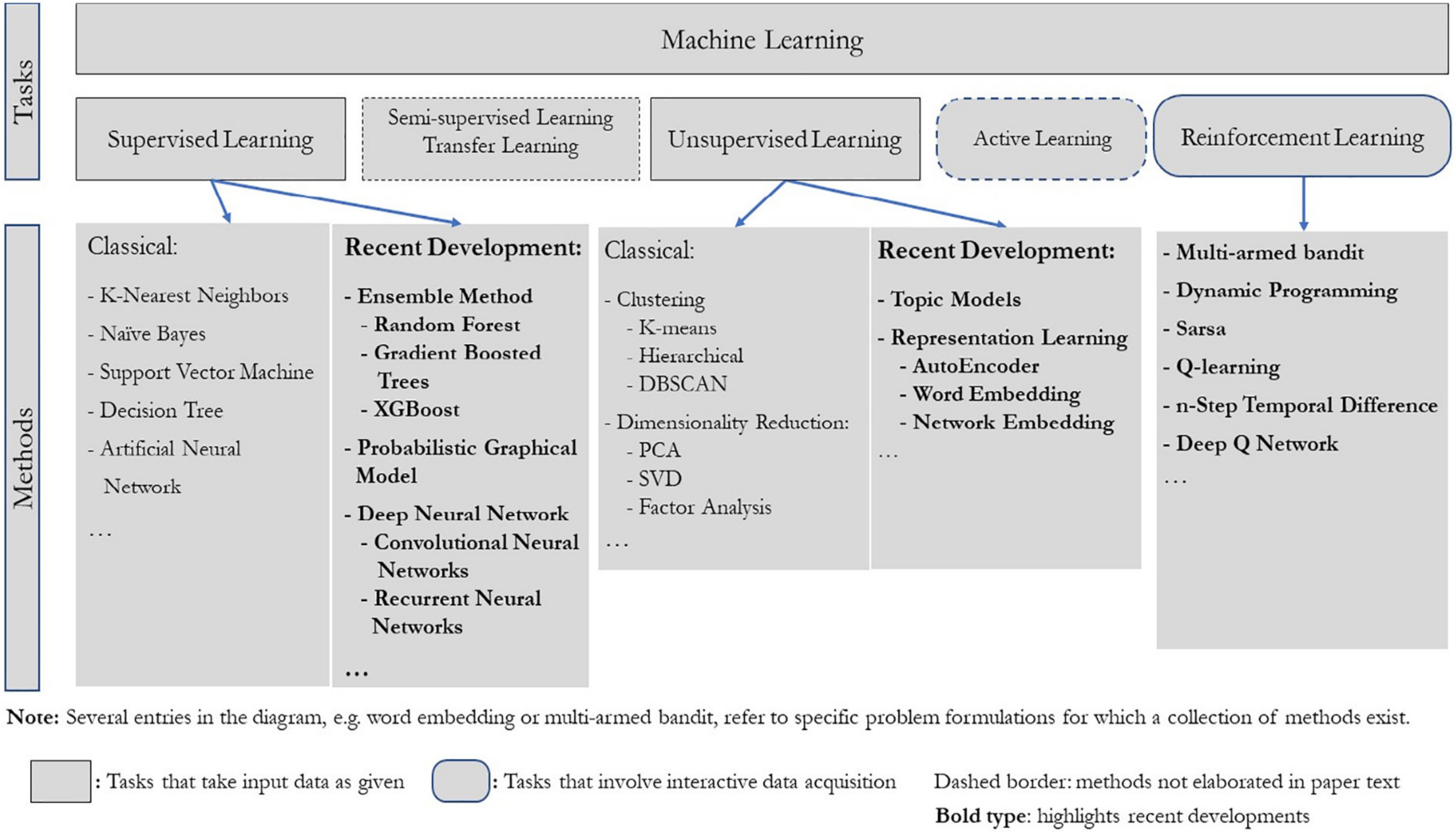
Maximum Entropy (ME)

Unsupervised Learning

Reinforcement Learning

Source: Jesus Serrano-Guerrero, Jose A. Olivas, Francisco P. Romero, and Enrique Herrera-Viedma (2015), "Sentiment analysis: A review and comparative analysis of web services," Information Sciences, 311, pp. 18-38.

Machine Learning Tasks and Methods



Tasks

Machine Learning

- Supervised Learning
- Semi-supervised Learning
Transfer Learning
- Unsupervised Learning
- Active Learning
- Reinforcement Learning

Methods

Supervised Learning:

Classical:

- K-Nearest Neighbors
- Naïve Bayes
- Support Vector Machine
- Decision Tree
- Artificial Neural Network

…

Recent Development:

- **Ensemble Method**
  - **Random Forest**
  - **Gradient Boosted Trees**
  - **XGBoost**
- **Probabilistic Graphical Model**
- **Deep Neural Network**
  - **Convolutional Neural Networks**
  - **Recurrent Neural Networks**

…

Unsupervised Learning:

Classical:

- Clustering
  - K-means
  - Hierarchical
  - DBSCAN
- Dimensionality Reduction:
  - PCA
  - SVD
  - Factor Analysis

…

Recent Development:

- **Topic Models**
- **Representation Learning**
  - **AutoEncoder**
  - **Word Embedding**
  - **Network Embedding**

…

Reinforcement Learning:

- **Multi-armed bandit**
- **Dynamic Programming**
- **Sarsa**
- **Q-learning**
- **n-Step Temporal Difference**
- **Deep Q Network**

…

Note: Several entries in the diagram, e.g. word embedding or multi-armed bandit, refer to specific problem formulations for which a collection of methods exist.

▭ : Tasks that take input data as given

▢ : Tasks that involve interactive data acquisition

Dashed border: methods not elaborated in paper text

Bold type: highlights recent developments

Source: Liye Ma and Baohong Sun (2020), "Machine learning and AI in marketing – Connecting computing power to human insights." International Journal of Research in Marketing, 37, no. 3, 481-504.

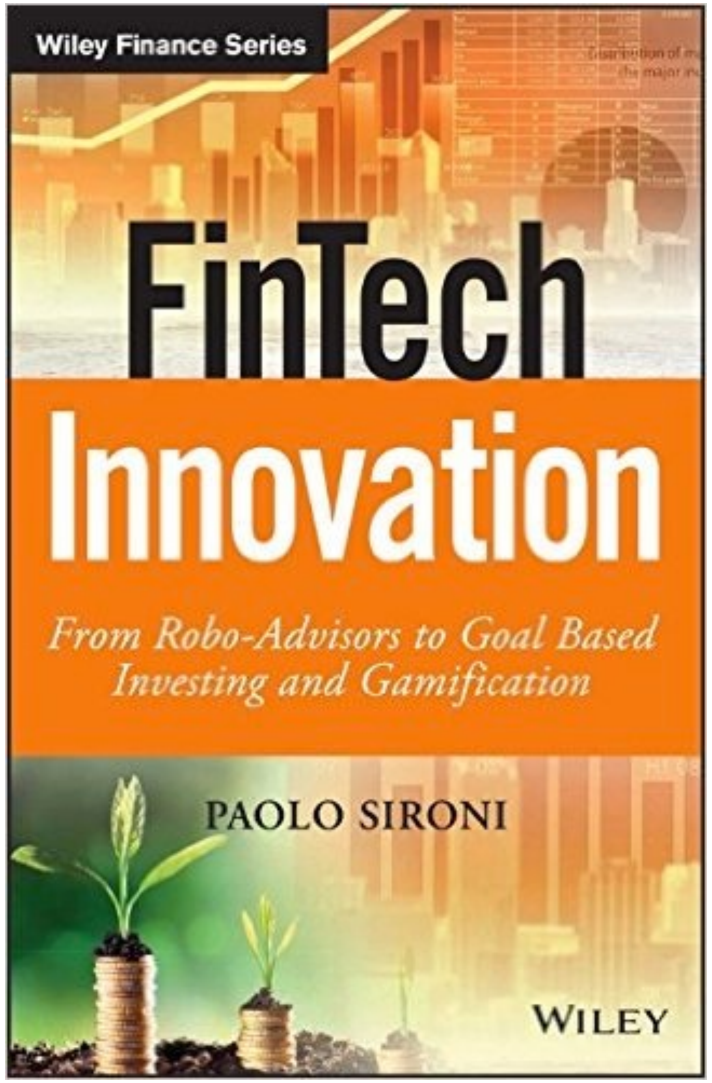
FinTech Innovation

Paolo Sironi (2016)

FinTech Innovation:

From Robo-Advisors to Goal Based Investing and Gamification,

Wiley



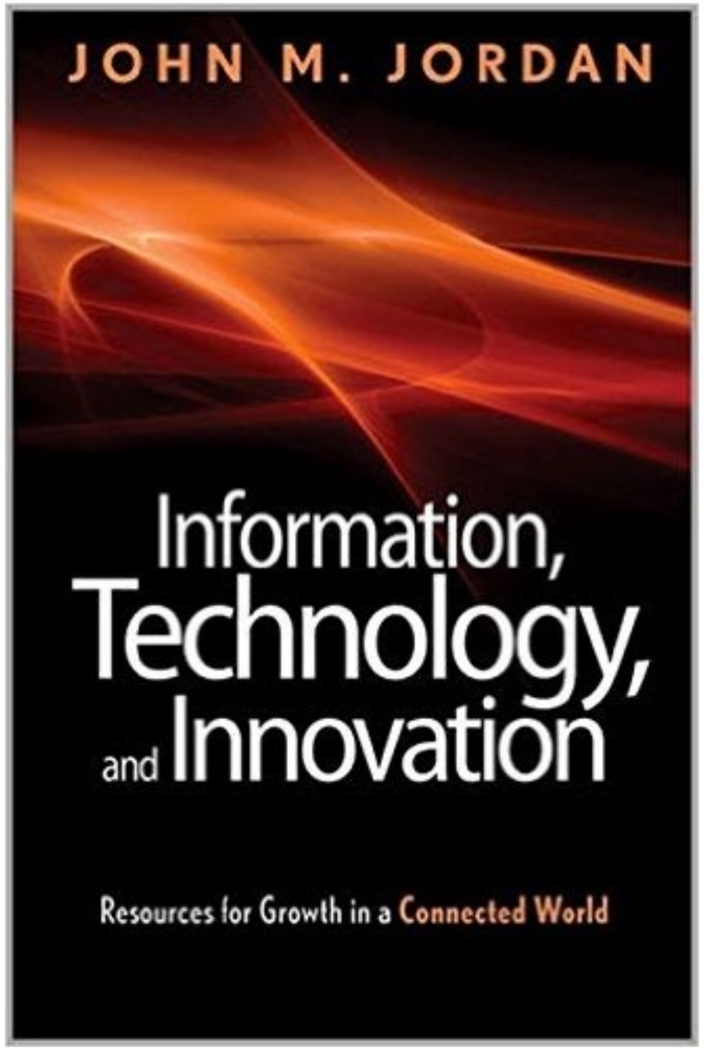
Source: https://www.amazon.com/FinTech-Innovation-Robo-Advisors-Investing-Gamification/dp/1119226988

John M. Jordan (2012),

Information, Technology, and Innovation:

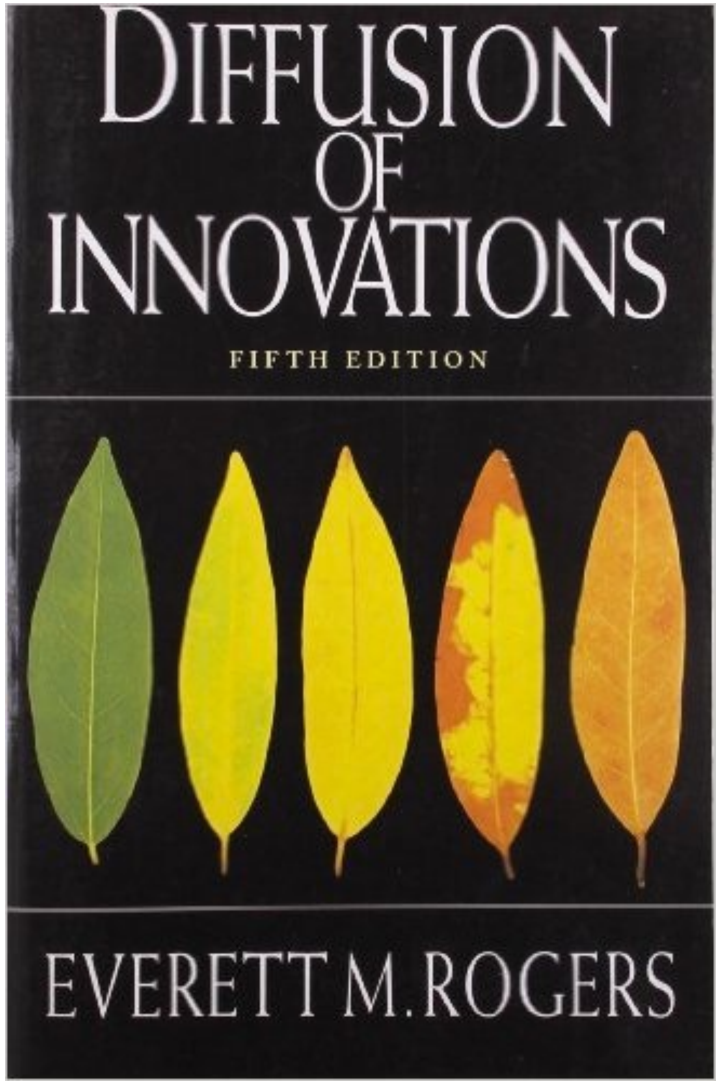
Resources for Growth in a Connected World,

Wiley



Source: https://www.amazon.com/Information-Technology-Innovation-Resources-Connected/dp/1118155785

Everett M. Rogers (2003),
Diffusion of Innovations,
5th Edition, Free Press



(Rogers,
1962;
1971;
1983;
1995;
2003)

Source: https://www.amazon.com/Diffusion-Innovations-5th-Everett-Rogers/dp/0743222091

Money and Financial History

- Why is a printed piece of paper worth anything?
- How can a coin be worth more or even less than the number stamped on it?
- Why is digital money real money?
- How can money be worth more or less than it was yesterday?

Source: Mike Thornton (2016), History of Money: Financial History: From Barter to Bitcoin - An Overview of Our Economic History, Monetary System & Currency Crisis, CreateSpace Independent Publishing Platform

Money

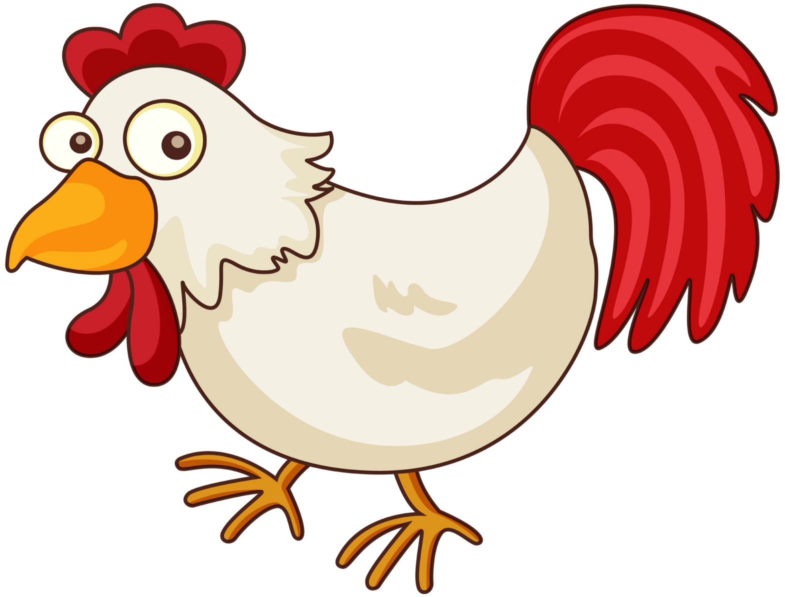
Exchange

Barter

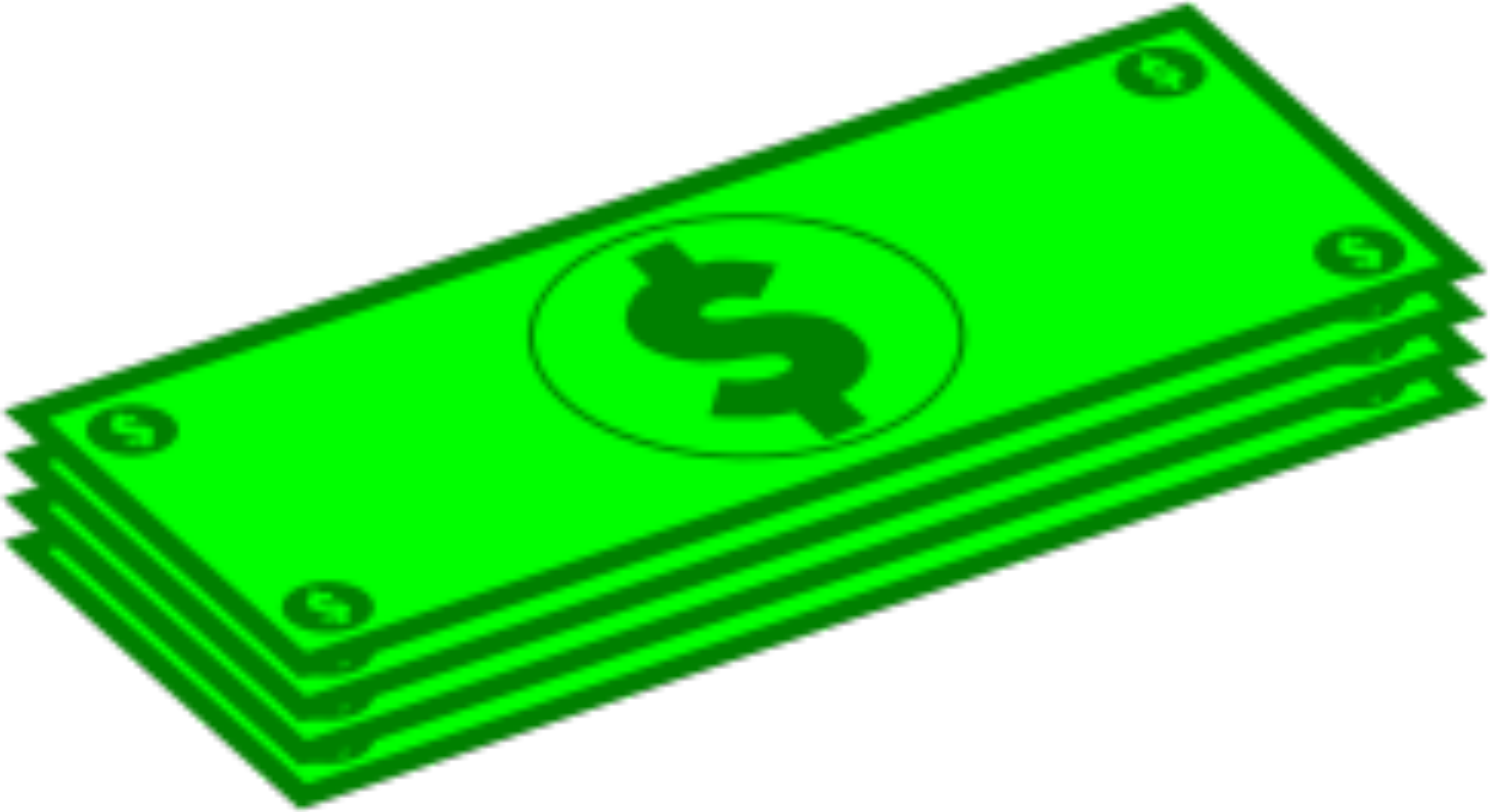
Barter

Source: https://www.jacksonvillebarter.com/

Barter



Money



Source: http://www.wpclipart.com/money/bills/bills_2/stack_of_bills_2.png.html

Bills

Source: http://www.wpclipart.com/money/bills/bills_2/stack_of_bills_2.png.html

Gold Bullion Coin

Source: http://www.wpclipart.com/money/coins/American_buffalo_gold_bullion_coin_front.jpg.html

Gold Bullion Coin

Source: http://www.wpclipart.com/money/coins/American_buffalo_gold_bullion_coin_back.jpg.html

Coin US Penny

Source: http://www.wpclipart.com/money/coins/coin_US_penny_2.png.html

Gold Bricks

Source: http://www.wpclipart.com/money/gold/gold_bricks_stacked.jpg.html

Digital
Money

Bitcoin (BTC)

Source: https://wpclipart.com/money/coins/bitcoin/bitcoin_gold.jpg.html

Ethereum (ETH)

Source: https://ethereum.org/en/

Tether (USDT)

Source: https://ethereum.org/en/stablecoins/

USDC

- **USDc** is probably the most famous **fiat-backed stablecoin**.
- Its value is roughly **a dollar** and it’s backed by **Circle and Coinbase**.

Source: https://ethereum.org/en/stablecoins/

Dai

- **Dai** is probably the most famous **decentralized stablecoin**.
- Its value is roughly **a dollar** and it’s accepted widely across **dapps**

Source: https://ethereum.org/en/stablecoins/

Financial Services

Financial Services

Source: http://www.wpclipart.com/money/credit_card/credit_card.png.html

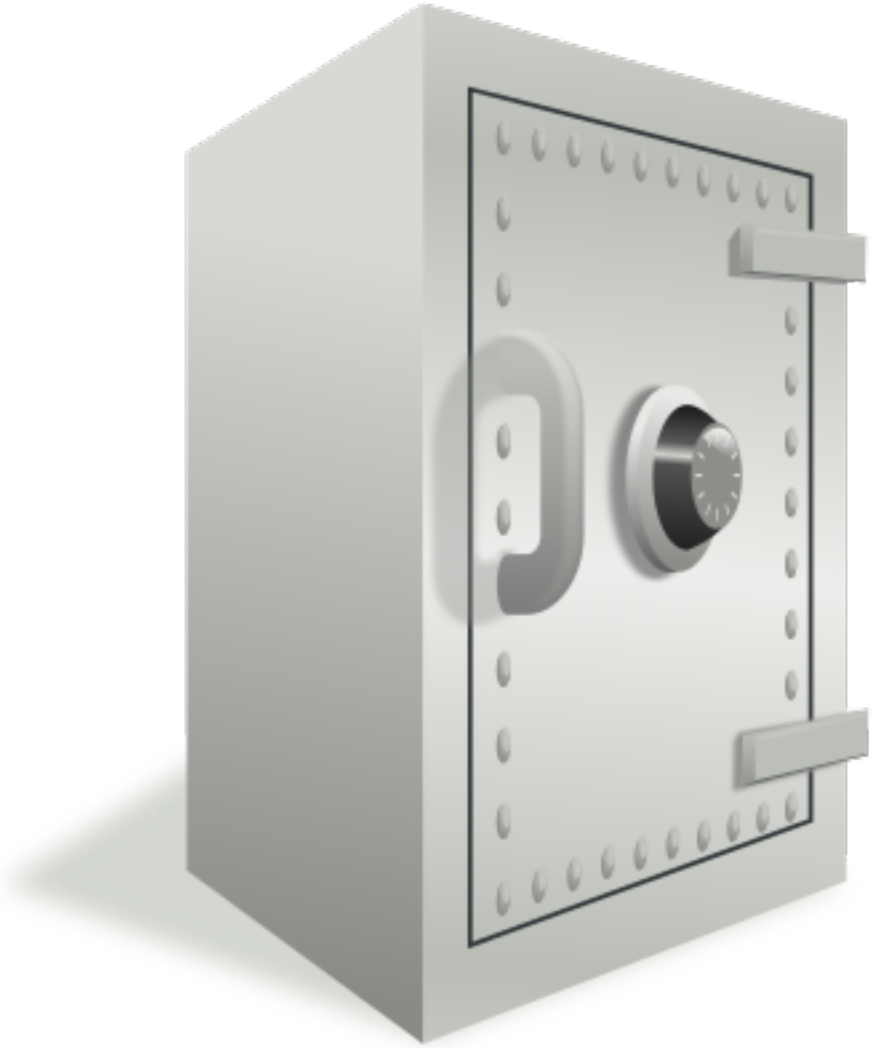
Financial Services

Source: http://www.wpclipart.com/working/icons/Accountant_bank_officer.png.html

Treasure

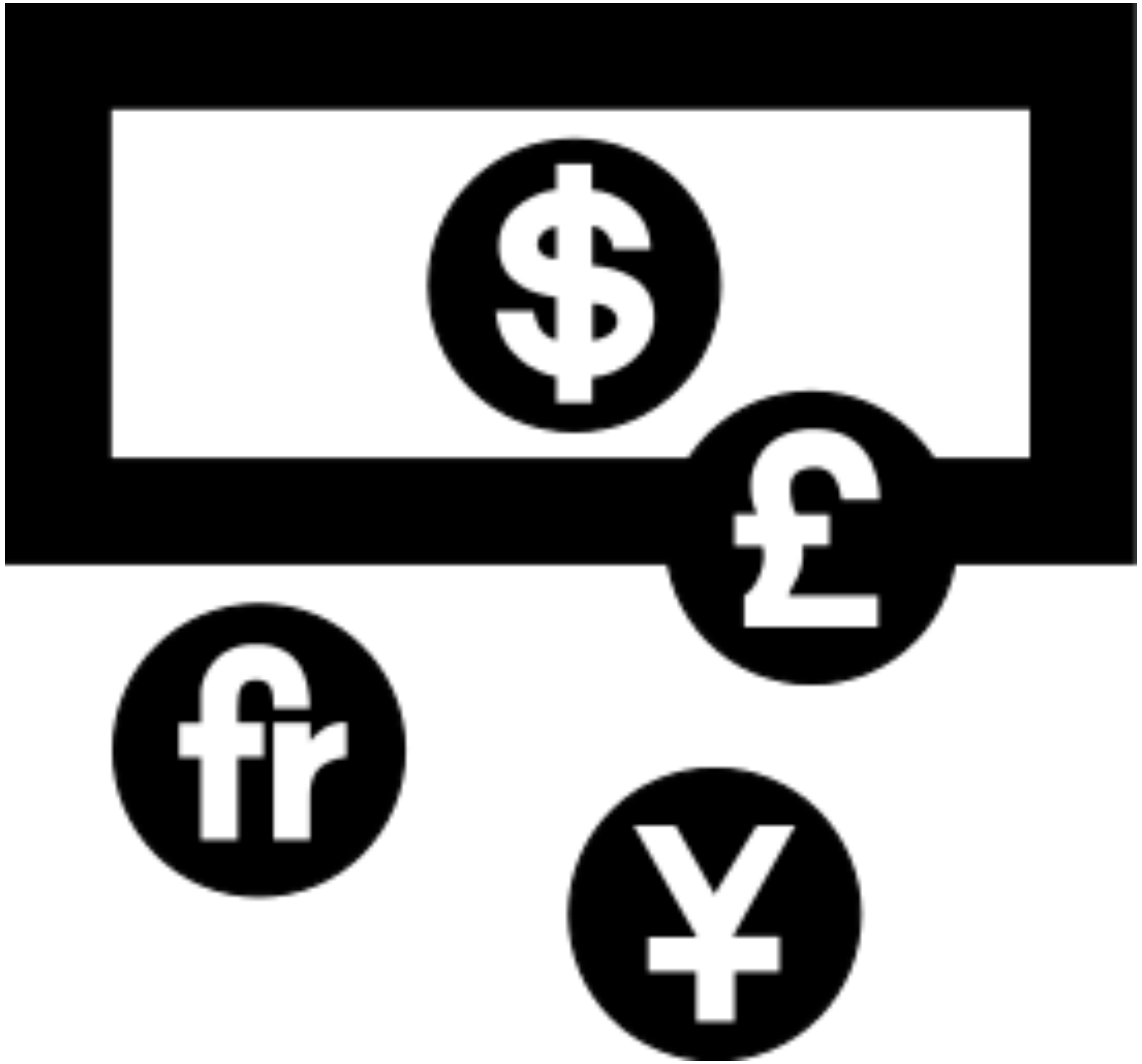
Source: http://www.wpclipart.com/money/treasure/treasure_chest_3.png.html

Safe



Source: http://www.wpclipart.com/money/safe/steel_safe.png.html

Currency Exchange



Source: http://www.wpclipart.com/signs_symbol/BW/travel_symbols/currency_exchange.png.html

Market

FinTech

Financial Technology
FinTech

“providing
financial services
by making use of
software and
modern technology”

Source: https://www.fintechweekly.com/fintech-definition

Financial Services

Financial Services

Source: http://www.crackitt.com/7-reasons-why-your-fintech-startup-needs-visual-marketing/

Financial Revolution with Fintech

A financial services revolution

Consumer Trends

1. Simplification
2. Transparency
3. Analytics
4. Reduced Friction

Source: http://www.hedgethink.com/fintech/european-fintech-top-100/

FinTech: Financial Services Innovation

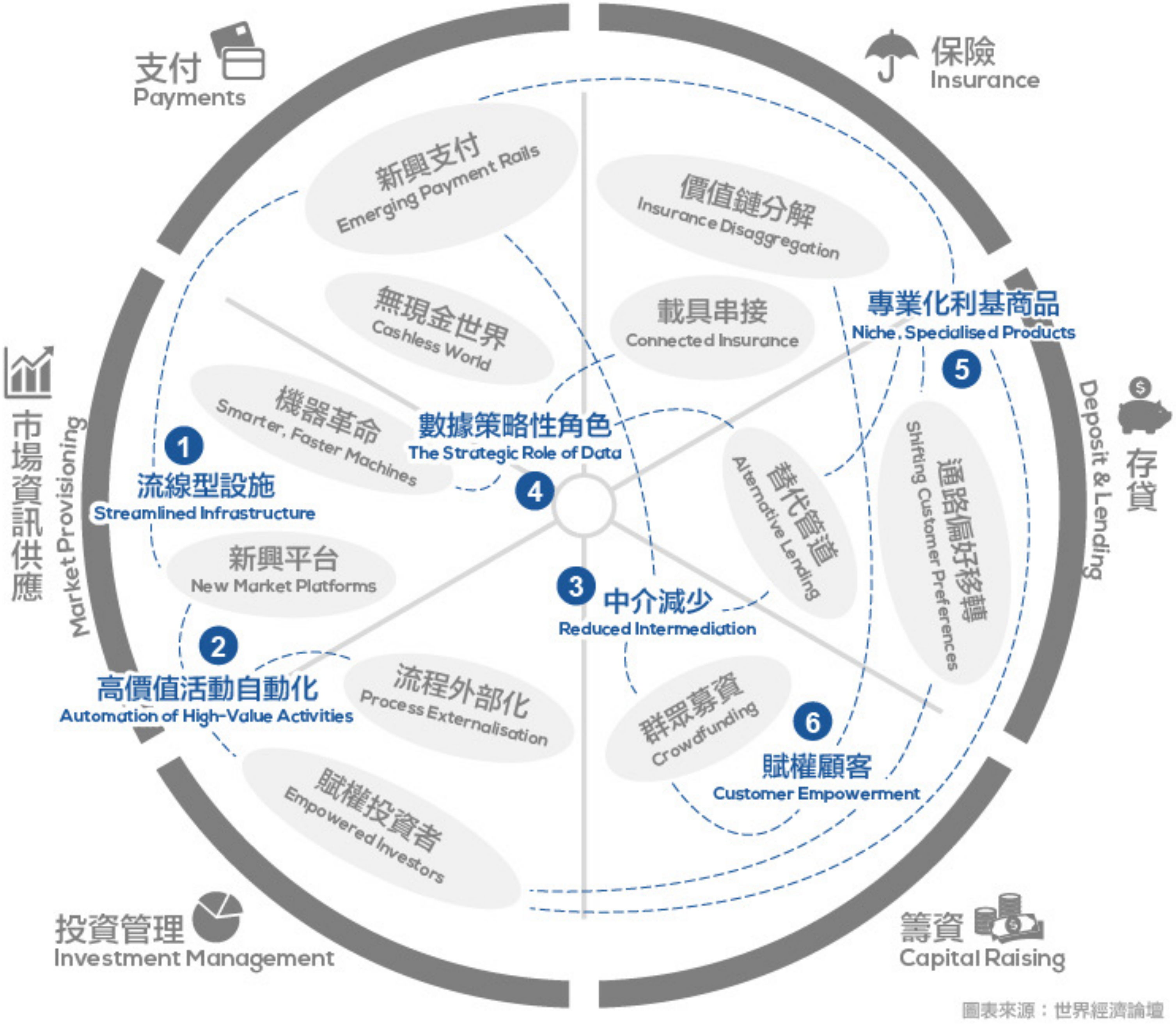
Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

FinTech:

Financial Services Innovation

1. Payments
2. Insurance
3. Deposits & Lending
4. Capital Raising
5. Investment Management
6. Market Provisioning

Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf



圖表來源：世界經濟論壇

Source: https://www.stockfeel.com.tw/2015年世界經濟論壇 - 未來的金融服務/

FinTech: Financial Services Innovation

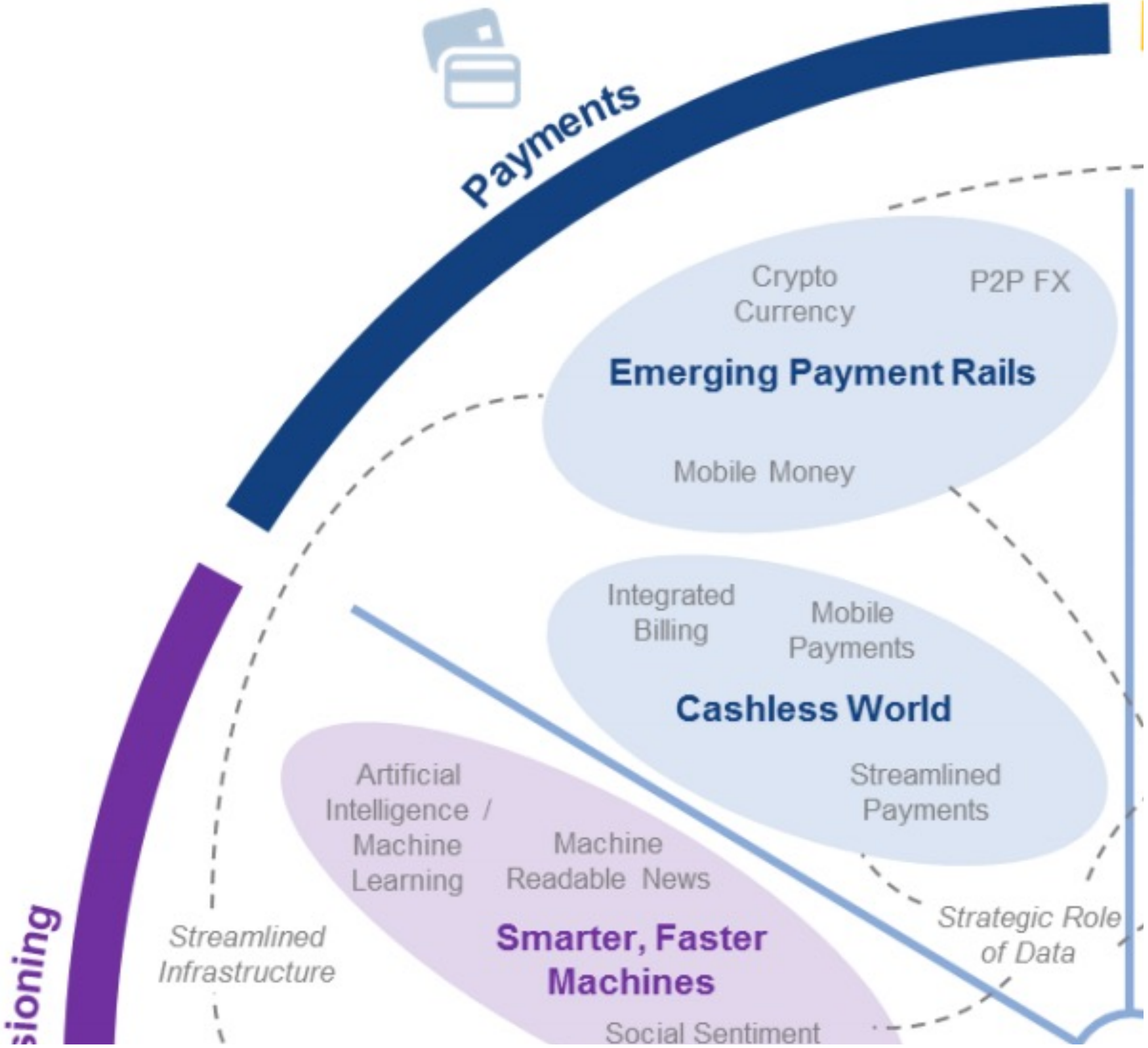
功能	創新項目
支付 Payments	無現金世界 (Cashless World) 新興支付 (Emerging Payment Rails)
保險 Insurance	價值鏈裂解 (Insurance Disaggregation) 保險串接裝置 (Connected Insurance)
存貸 Deposit & Lending	替代管道 (Alternative Lending) 通路偏好移轉 (Shifting Customer Preferences)
籌資 Capital Raising	群眾募資 (Crowdfunding)
投資管理 Investment Management	賦權投資者 (Empowered Investors) 流程外部化 (Process Externalisation)
市場資訊供應 Market Provisioning	機器革命 (Smarter, Faster Machines) 新興平台 (New Market Platforms)

圖表來源：Fugle團隊整理

Source: https://www.stockfeel.com.tw/2015年世界經濟論壇 - 未來的金融服務/

1

FinTech: Payment



Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

1

FinTech: Payment
Cashless World
Emerging Payment Rails

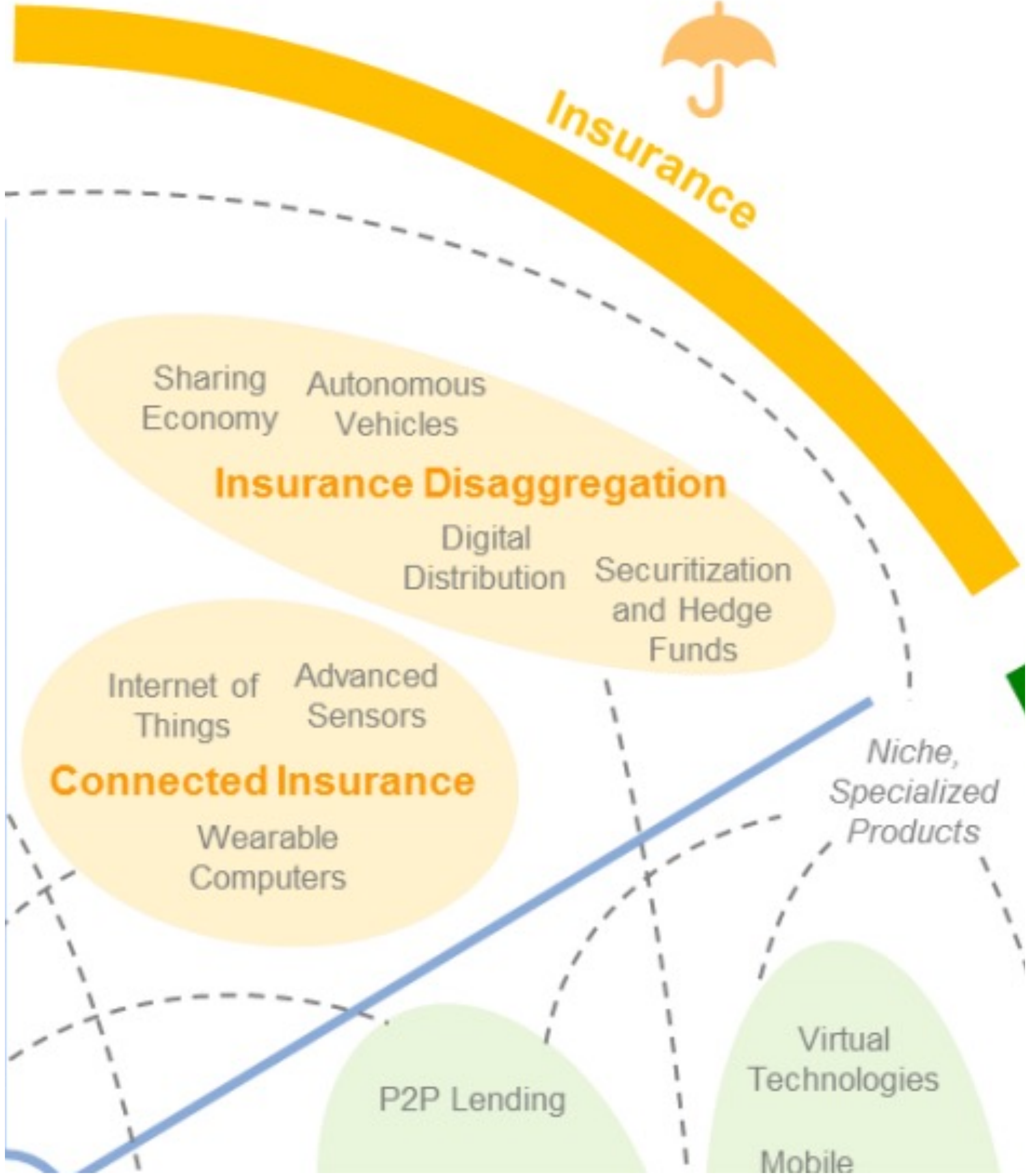
	創新	關鍵趨勢
支付	無現金世界 Cashless World	流線型支付（Streamlined Payment）、次世代安全（Next Generation Security）、帳單整合、手機支付
	新興支付 Emerging Payment Rails	密碼協定（Cryptographic Protocols）、行動錢包、P2P

圖表來源：Fugle團隊整理

Source: https://www.stockfeel.com.tw/2015年世界經濟論壇 - 未來的金融服務/

2

FinTech: Insurance



Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

2

FinTech: Insurance
Insurance Disaggregation
Connected Insurance

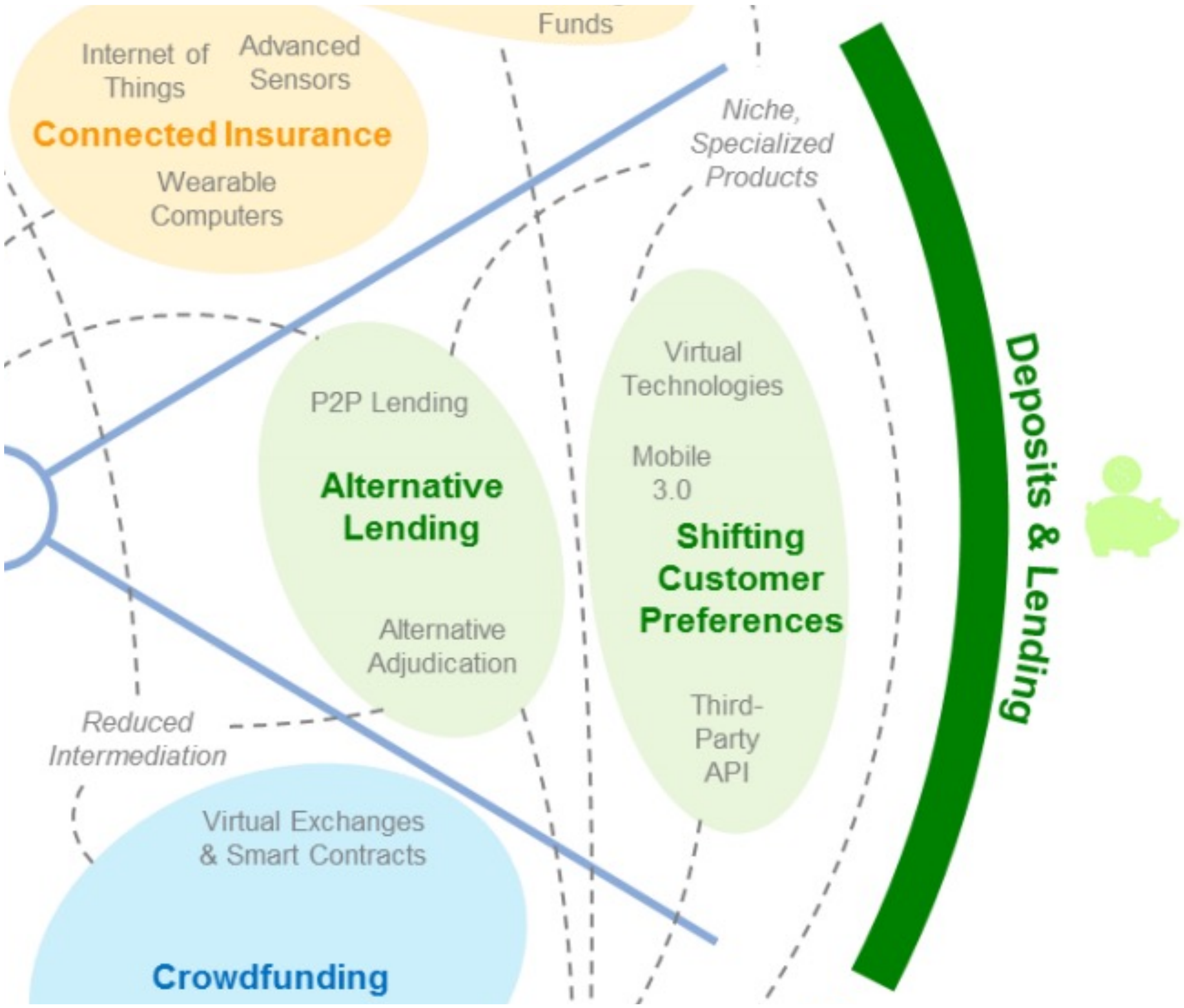
保險

創新	關鍵趨勢
價值鏈裂解 Insurance Disaggregation	裂解分佈（Disaggregated Distribution）、共享經濟、第三方資本、自動駕駛車
保險串接裝置 Connected Insurance	高性價比感測器、穿戴式裝置、物聯網、標準化平台

圖表來源：Fugle團隊整理

Source: https://www.stockfeel.com.tw/2015年世界經濟論壇 - 未來的金融服務/

3 FinTech: Deposits & Lending



Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

3

FinTech: Deposits & Lending
Alternative Lending
Shifting Customer Preferences

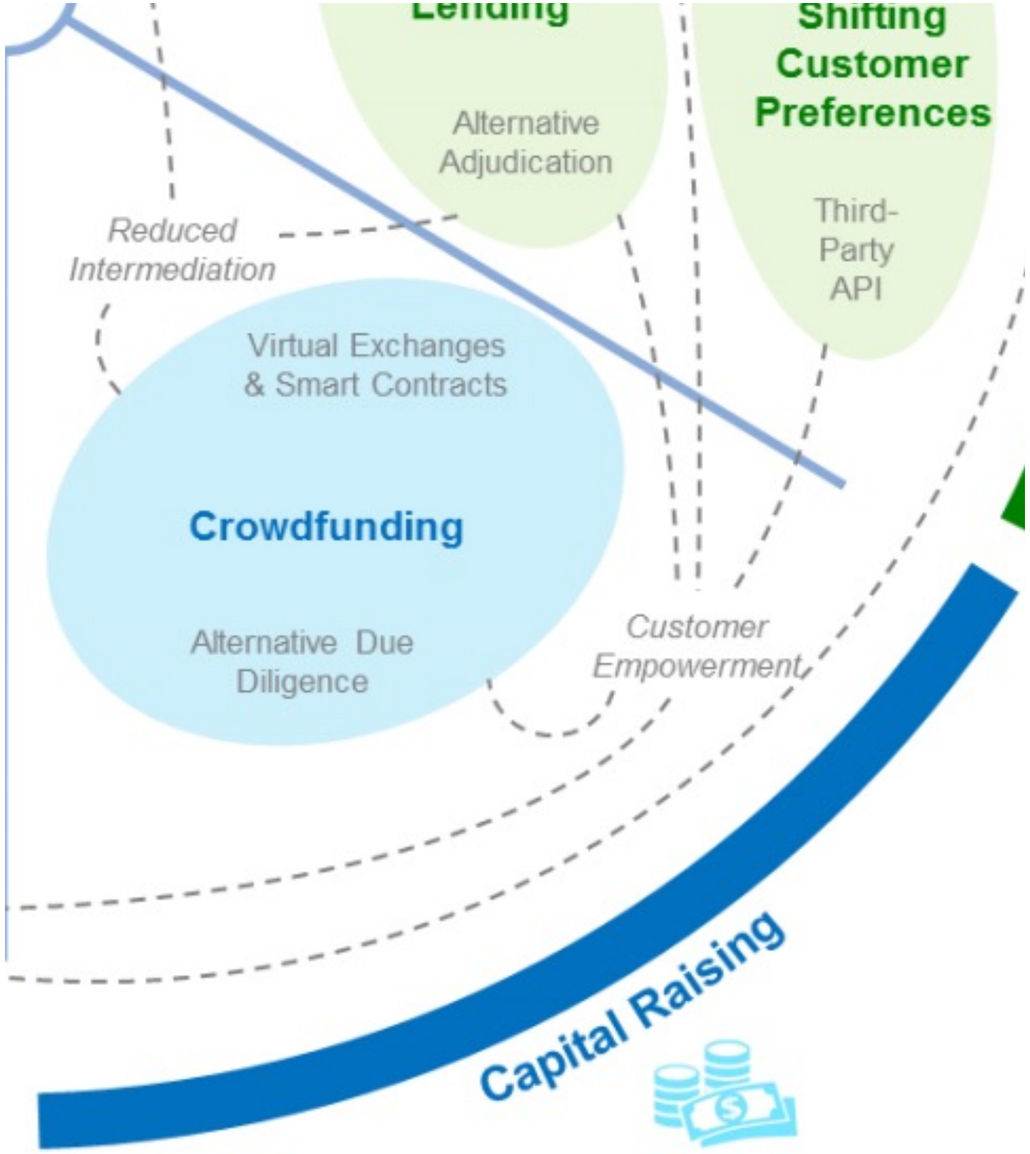
	創新	關鍵趨勢
存貸	替代管道 Alternative Lending	另類仲裁（Alternative Adjudication）、自動化流程、P2P
	通路偏好移轉 Shifting Customer Preferences	虛擬銀行 2.0、銀行即平台：API、行動銀行進化

圖表來源：Fugle團隊整理

Source: https://www.stockfeel.com.tw/2015年世界經濟論壇 - 未來的金融服務/

4

FinTech: Capital Raising



Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

4

FinTech: Capital Raising
Crowdfunding

創新

關鍵趨勢

籌資

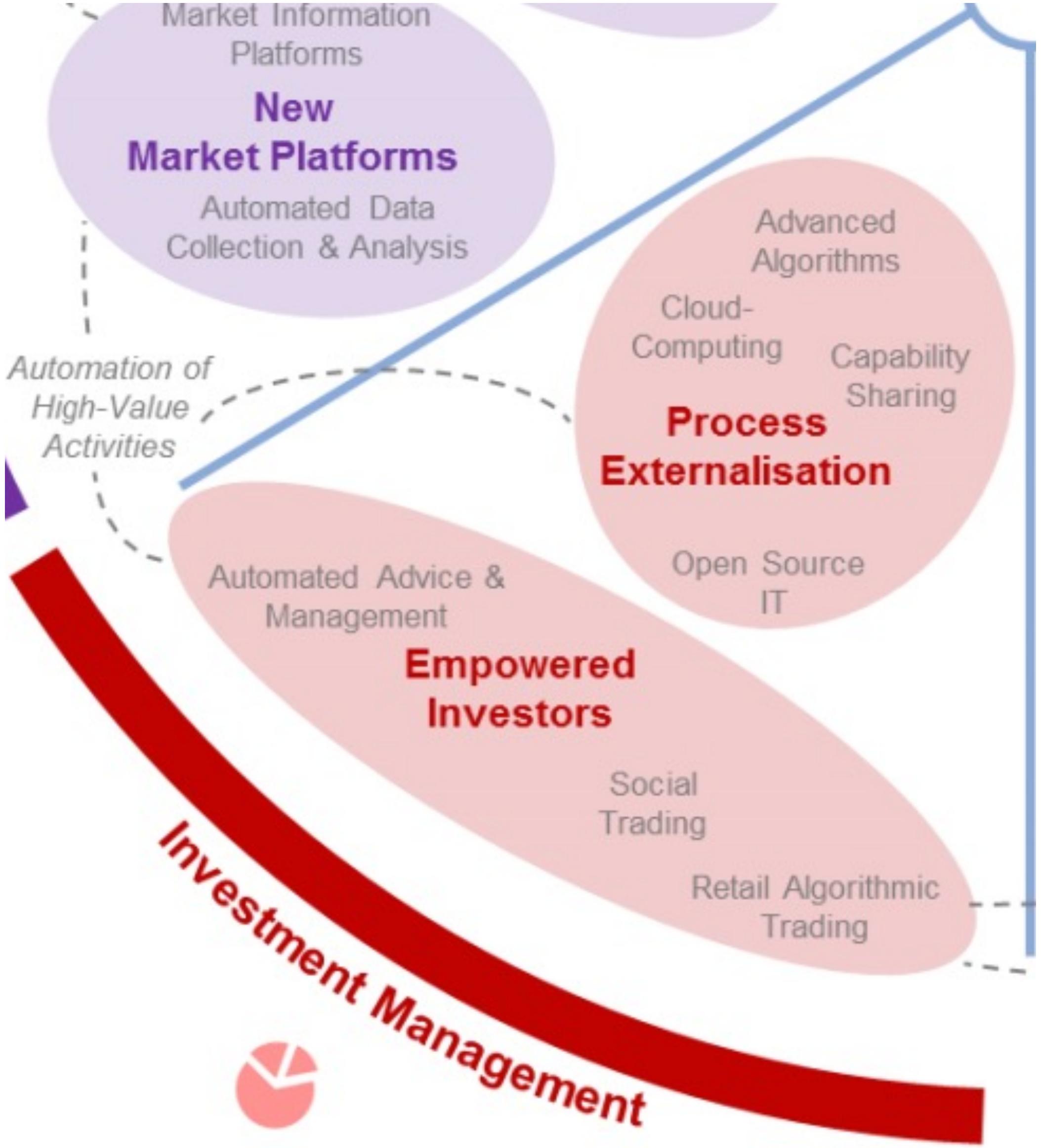
群眾募資
Crowdfunding

另類仲裁（Alternative Adjudication）、賦權天使投資者 (Empowered Angel Investors)

圖表來源：Fugle團隊整理

Source: https://www.stockfeel.com.tw/2015年世界經濟論壇 - 未來的金融服務/

5 FinTech: Investment Management



Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

5 FinTech: Investment Management

Empowered Investors

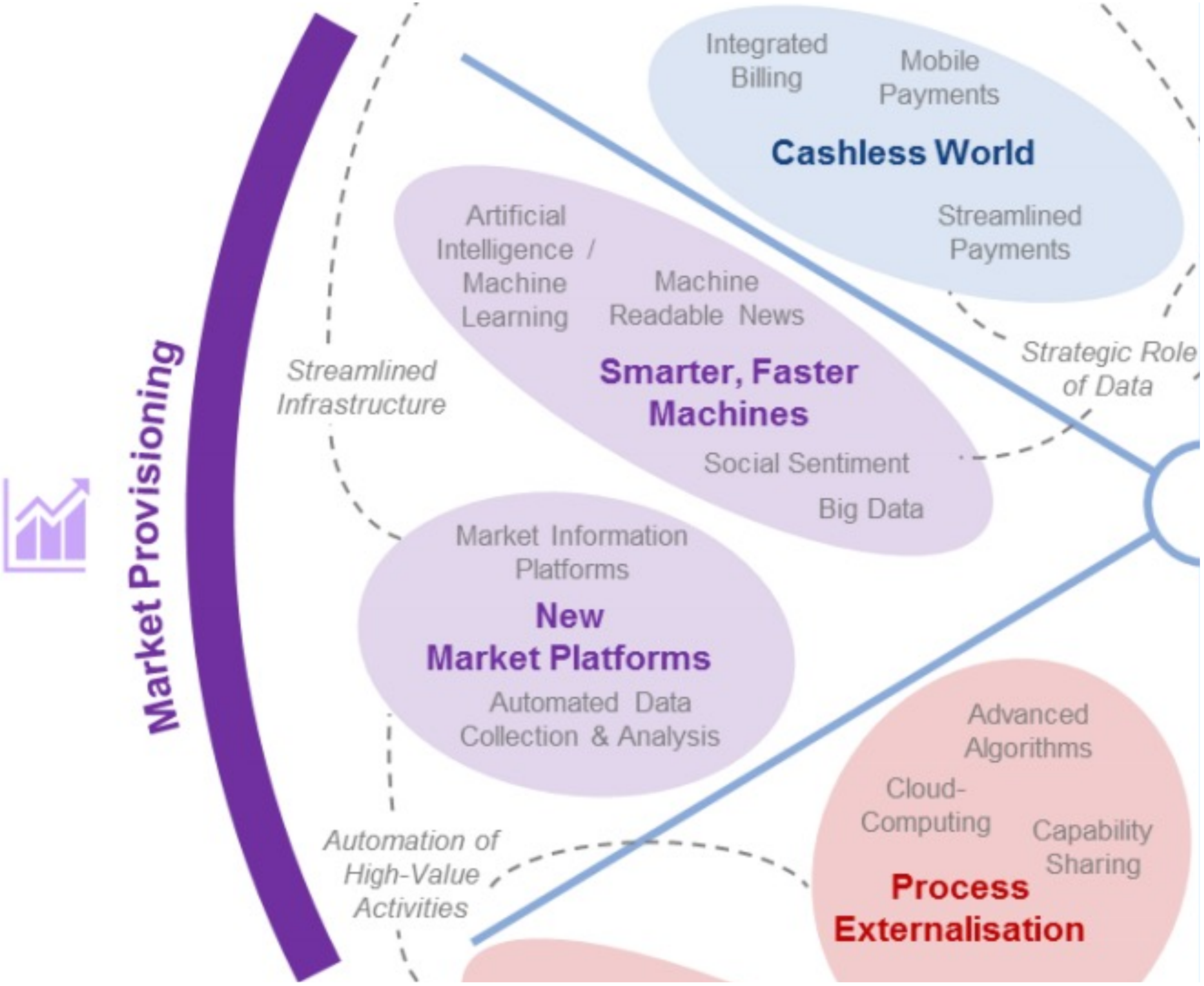
Process Externalization

	創新	關鍵趨勢
投資管理	賦權投資者 Empowered Investors	社群交易、機器推薦與財富管理、零售演算法交易 (Retail Algorithmic Trading)
	流程外部化 Process Externalisation	流程即服務 (Process-as-a-Service, PaaS)、能力共享 (Capability Sharing)、進階分析、自然語言

圖表來源：Fugle團隊整理

Source: https://www.stockfeel.com.tw/2015年世界經濟論壇 - 未來的金融服務/

6 FinTech: Market Provisioning



Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

6

FinTech: Market Provisioning
Smarter, Faster Machines
New Market Platforms

市場資訊供應

創新	關鍵趨勢
機器革命 Smarter, Faster Machines	機器易用數據（Machine Accessible Data）、人工智慧 / 機器學習、大數據
新興平台 New Market Platforms	固定收益商品平台 ALGOMI、基金 / 組合型基金平台 NOVUS、私募 / 創投平台 BISON、未公發股權平台 LIQUITY、原物料商品與衍生性合約平台 ClauseMatch

圖表來源：Fugle團隊整理

Source: https://www.stockfeel.com.tw/2015年世界經濟論壇 - 未來的金融服務/

Decentralized Finance (DeFi)

Block Chain FinTech

Decentralized Finance (DeFi)

- A global, open alternative to the current financial system.
- Products that let you borrow, save, invest, trade, and more.
- Based on open-source technology that anyone can program with.

Source: https://ethereum.org/en/defi/

Traditional Finance
Centralized Finance (CeFi)

- Some people aren't granted access to set up a bank account or use financial services.
- Lack of access to financial services can prevent people from being employable.
- Financial services can block you from getting paid.
- A hidden charge of financial services is your personal data.
- Governments and centralized institutions can close down markets at will.
- Trading hours often limited to business hours of specific time zone.
- Money transfers can take days due to internal human processes.
- There's a premium to financial services because intermediary institutions need their cut.

Source: https://ethereum.org/en/defi/

DeFi vs. CeFi

Decentralized Finance (DeFi)	Traditional Finance (Centralized Finance; CeFi)
You hold your money.	Your money is held by companies.
You control where your money goes and how it's spent.	You have to trust companies not to mismanage your money, like lend to risky borrowers.
Transfers of funds happen in minutes.	Payments can take days due to manual processes.
Transaction activity is pseudonymous.	Financial activity is tightly coupled with your identity.
DeFi is open to anyone.	You must apply to use financial services.
The markets are always open.	Markets close because employees need breaks.
It's built on transparency – anyone can look at a product's data and inspect how the system works.	Financial institutions are closed books: you can't ask to see their loan history, a record of their managed assets, and so on.

Source: https://ethereum.org/en/defi/

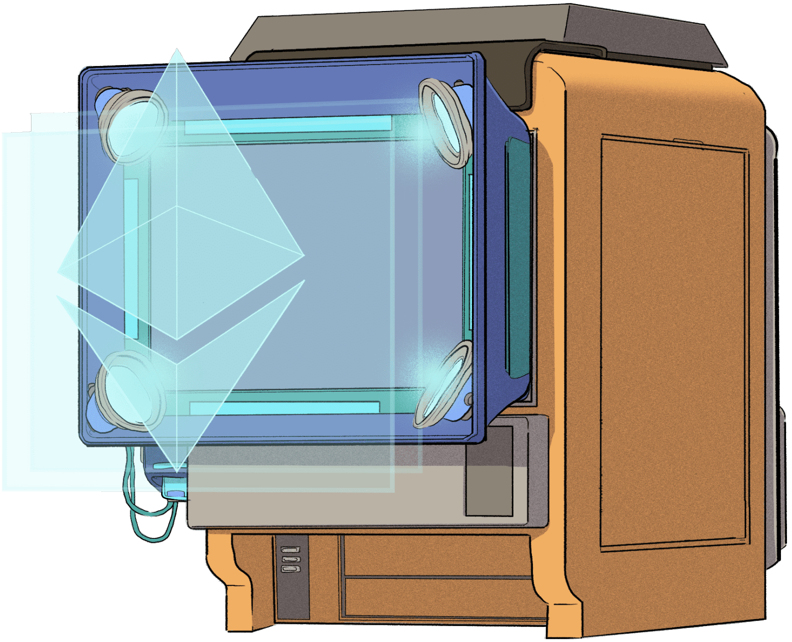
(DeFi)
Decentralized Applications (Dapps)

- Ethereum-powered tools and services
- Dapps are a growing movement of applications that use Ethereum to disrupt business models or invent new ones

Source: https://ethereum.org/en/defi/

The Internet of Assets

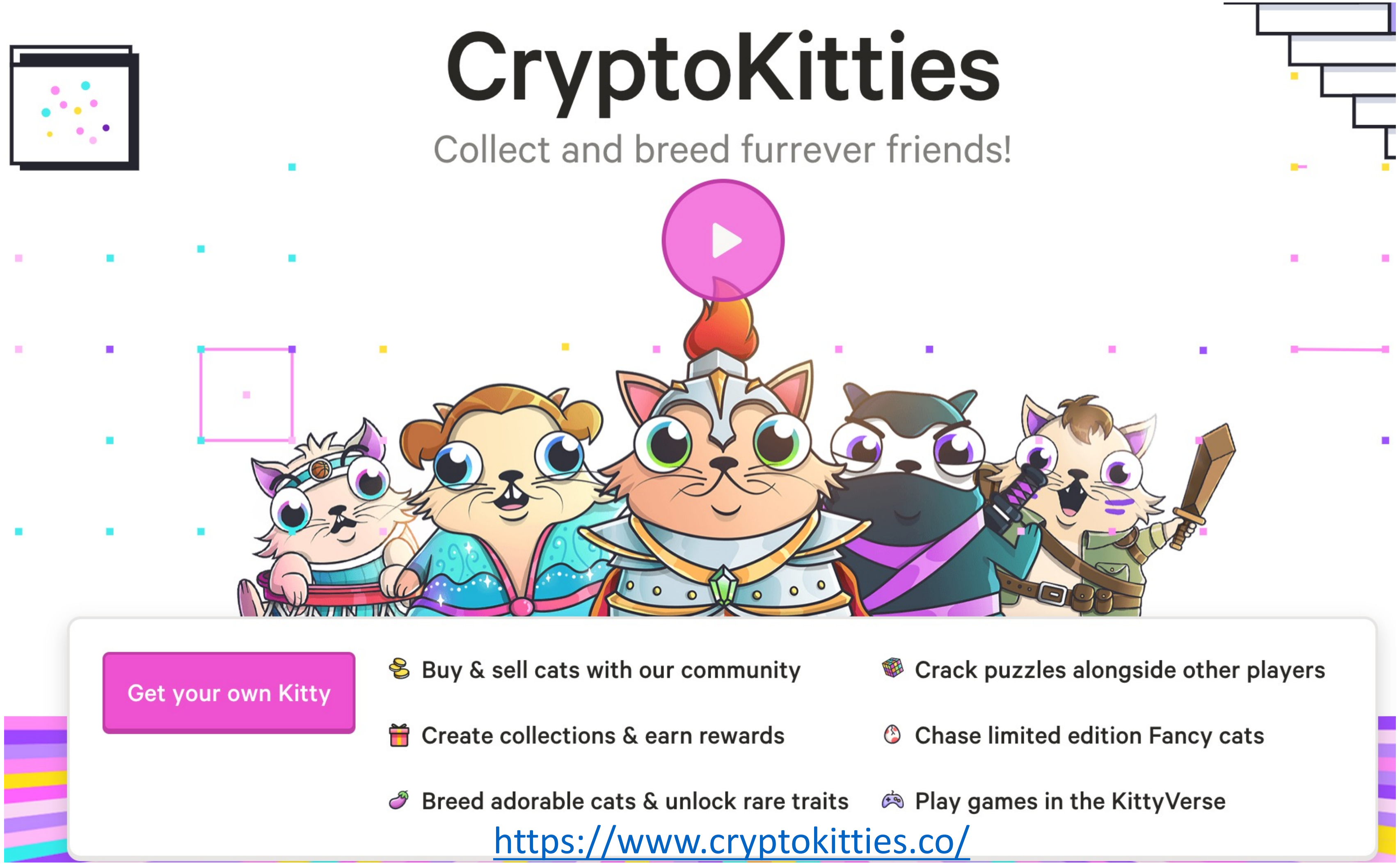
- **Ethereum** isn't just for **digital money**.
- Anything you can own can be **represented**, **traded** and **put to use** as **non-fungible tokens (NFTs)**.



Source: https://ethereum.org/en/defi/

Non-Fungible Tokens (NFT)

CryptoKitties



CryptoKitties

Collect and breed furrever friends!

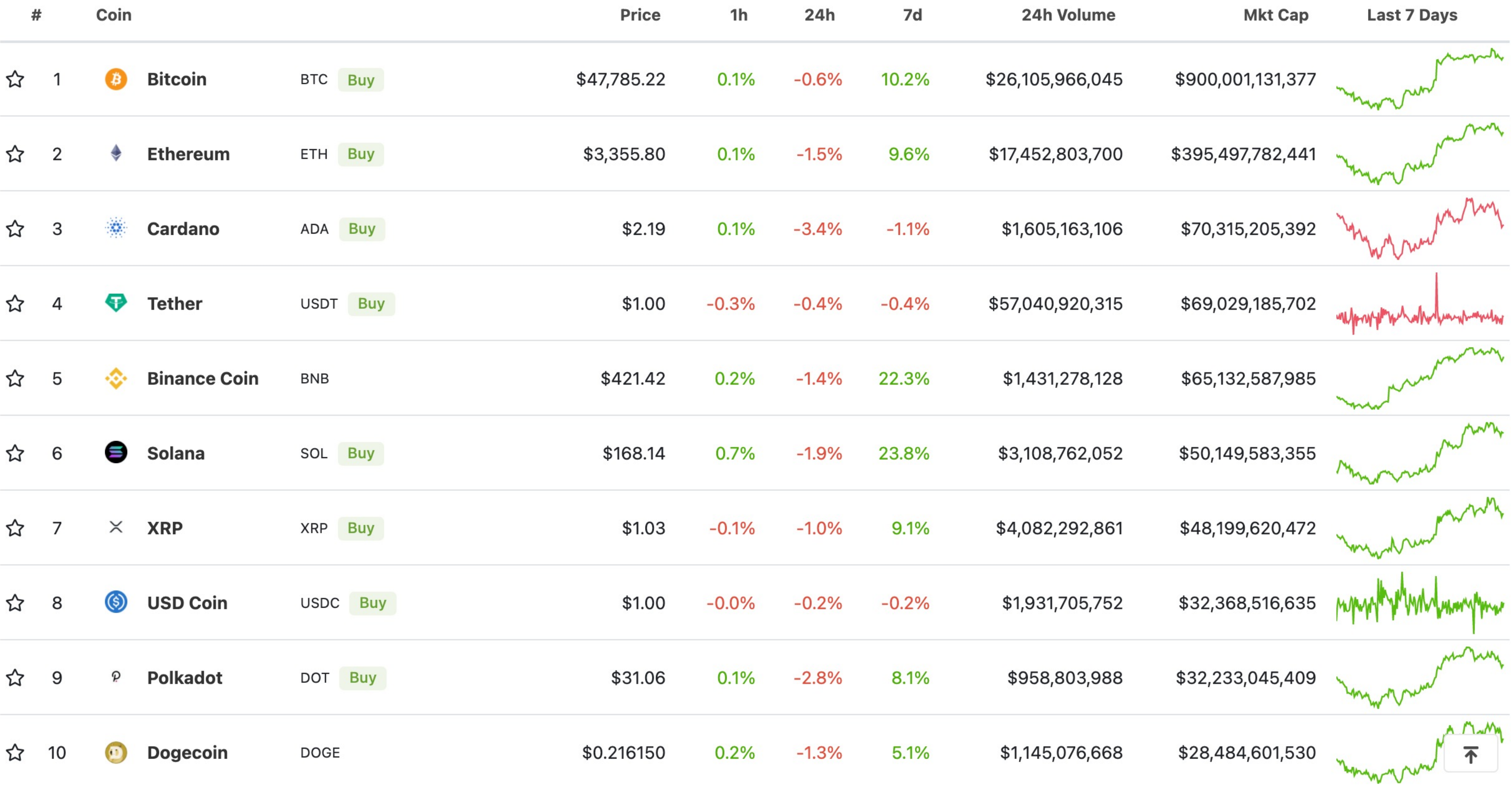
- Buy & sell cats with our community
- Create collections & earn rewards
- Breed adorable cats & unlock rare traits
- Crack puzzles alongside other players
- Chase limited edition Fancy cats
- Play games in the KittyVerse

https://www.cryptokitties.co/

Source: Matt Fortnow and QuHarrison Terry (2021), The NFT Handbook - How to Create, Sell and Buy Non-Fungible Tokens, Wiley

Top 10 Cryptocurrency Prices by Market Cap

The global cryptocurrency market cap today is $2.2 Trillion (2021/10/04)



	#	Coin			Price	1h	24h	7d	24h Volume	Mkt Cap	Last 7 Days
☆	1	**Bitcoin**	BTC	Buy	$47,785.22	0.1%	-0.6%	10.2%	$26,105,966,045	$900,001,131,377	
☆	2	**Ethereum**	ETH	Buy	$3,355.80	0.1%	-1.5%	9.6%	$17,452,803,700	$395,497,782,441	
☆	3	**Cardano**	ADA	Buy	$2.19	0.1%	-3.4%	-1.1%	$1,605,163,106	$70,315,205,392	
☆	4	**Tether**	USDT	Buy	$1.00	-0.3%	-0.4%	-0.4%	$57,040,920,315	$69,029,185,702	
☆	5	**Binance Coin**	BNB		$421.42	0.2%	-1.4%	22.3%	$1,431,278,128	$65,132,587,985	
☆	6	**Solana**	SOL	Buy	$168.14	0.7%	-1.9%	23.8%	$3,108,762,052	$50,149,583,355	
☆	7	**XRP**	XRP	Buy	$1.03	-0.1%	-1.0%	9.1%	$4,082,292,861	$48,199,620,472	
☆	8	**USD Coin**	USDC	Buy	$1.00	-0.0%	-0.2%	-0.2%	$1,931,705,752	$32,368,516,635	
☆	9	**Polkadot**	DOT	Buy	$31.06	0.1%	-2.8%	8.1%	$958,803,988	$32,233,045,409	
☆	10	**Dogecoin**	DOGE		$0.216150	0.2%	-1.3%	5.1%	$1,145,076,668	$28,484,601,530	

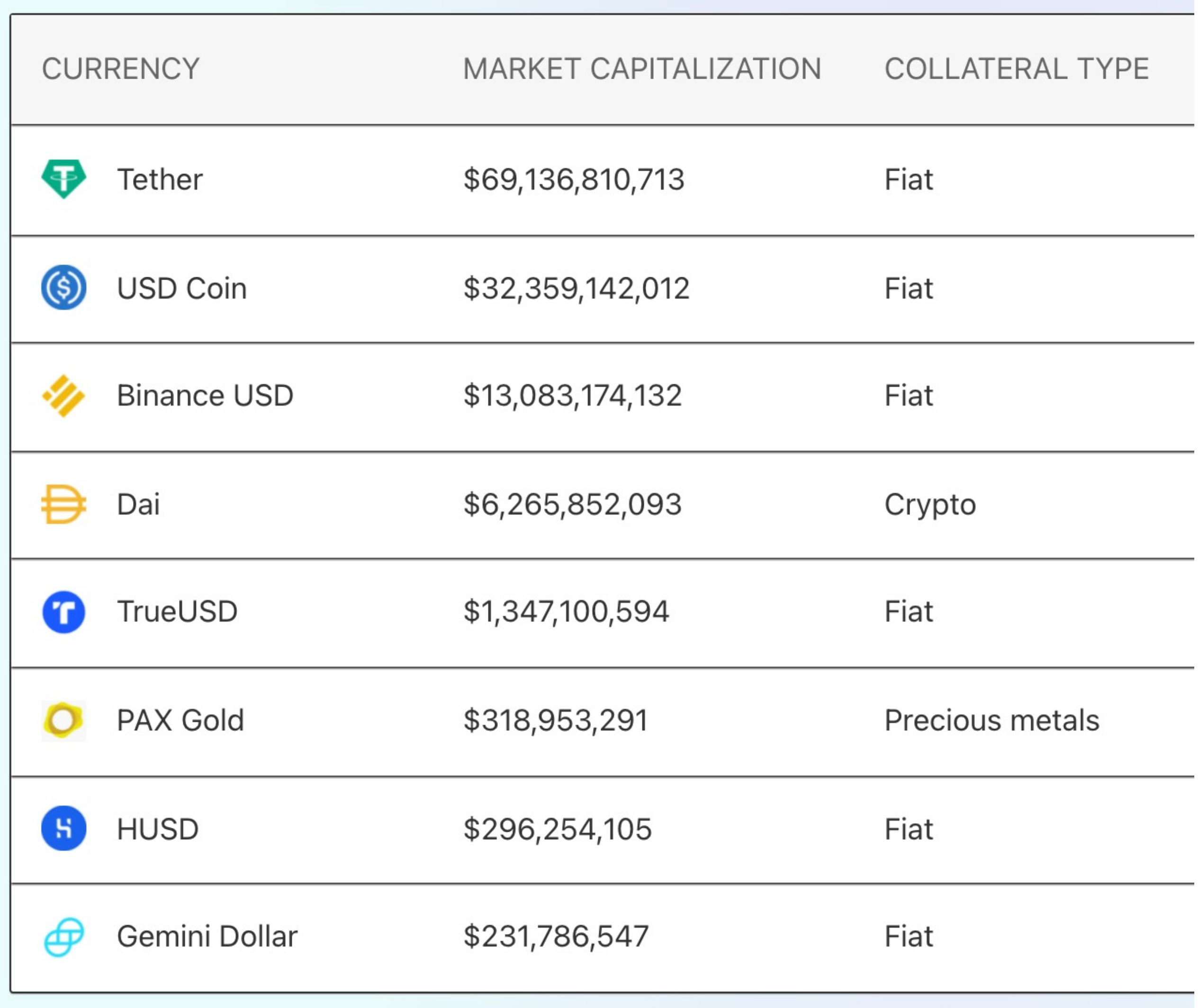
Source: https://www.coingecko.com/en

Top Stablecoins

(Tether USDT, USD Coin USDC, Dai)

Digital money for everyday use

Stablecoins are
Ethereum tokens designed to
stay at a fixed value,
even when
the price of ETH changes.

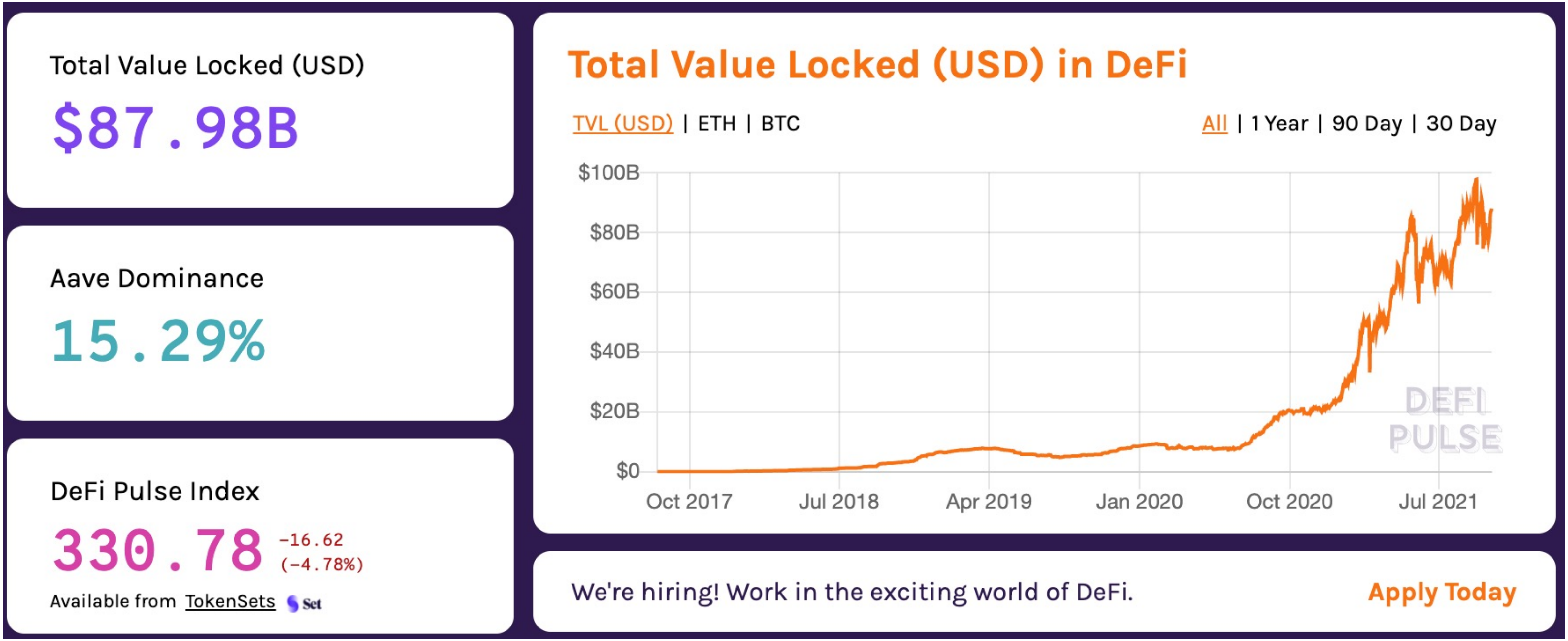


CURRENCY	MARKET CAPITALIZATION	COLLATERAL TYPE
Tether	$69,136,810,713	Fiat
USD Coin	$32,359,142,012	Fiat
Binance USD	$13,083,174,132	Fiat
Dai	$6,265,852,093	Crypto
TrueUSD	$1,347,100,594	Fiat
PAX Gold	$318,953,291	Precious metals
HUSD	$296,254,105	Fiat
Gemini Dollar	$231,786,547	Fiat

Source: https://ethereum.org/en/stablecoins/

DeFi Total Value Locked (USD)

(DeFi Pulse)



Total Value Locked (USD)

$87.98B

Aave Dominance

15.29%

DeFi Pulse Index

330.78 -16.62 (-4.78%)

Available from TokenSets Set

Total Value Locked (USD) in DeFi

TVL (USD) | ETH | BTC

All | 1 Year | 90 Day | 30 Day

We're hiring! Work in the exciting world of DeFi. **Apply Today**

Source: https://defipulse.com/

Top 10 DeFi Applications (DApps)

(DeFi Pulse)

Lending

DEXes (Decentralized Exchanges)

Assets

Derivatives

Payments

	DeFi Paulse	DeFi Apps Name	Chain	Category	Locked (USD)
🏆	1.	**Aave**	Multichain	Lending	$15.22B
🥈	2.	**Maker**	Ethereum	Lending	$12.85B
🥉	3.	**Curve Finance**	Multichain	DEXes	$12.75B
	4.	**InstaDApp**	Ethereum	Lending	$11.32B
	5.	**Compound**	Ethereum	Lending	$9.56B
	6.	**Uniswap**	Ethereum	DEXes	$6.50B
	7.	**Convex Finance**	Ethereum	Assets	$6.40B
	8.	**yearn.finance**	Ethereum	Assets	$4.31B
	9.	**SushiSwap**	Ethereum	DEXes	$3.97B
	10.	**Liquity**	Ethereum	Lending	$2.28B

Source: https://defipulse.com/

Financial Stability Challenges

Crypto Ecosystem

- Operational, cyber, and governance risks
- Integrity (market and AML/CFT)
  (Anti–Money Laundering / Combating the Financing of Terrorism)
- Data availability / reliability
- Challenges from cross-boarder activites

Stablecoins

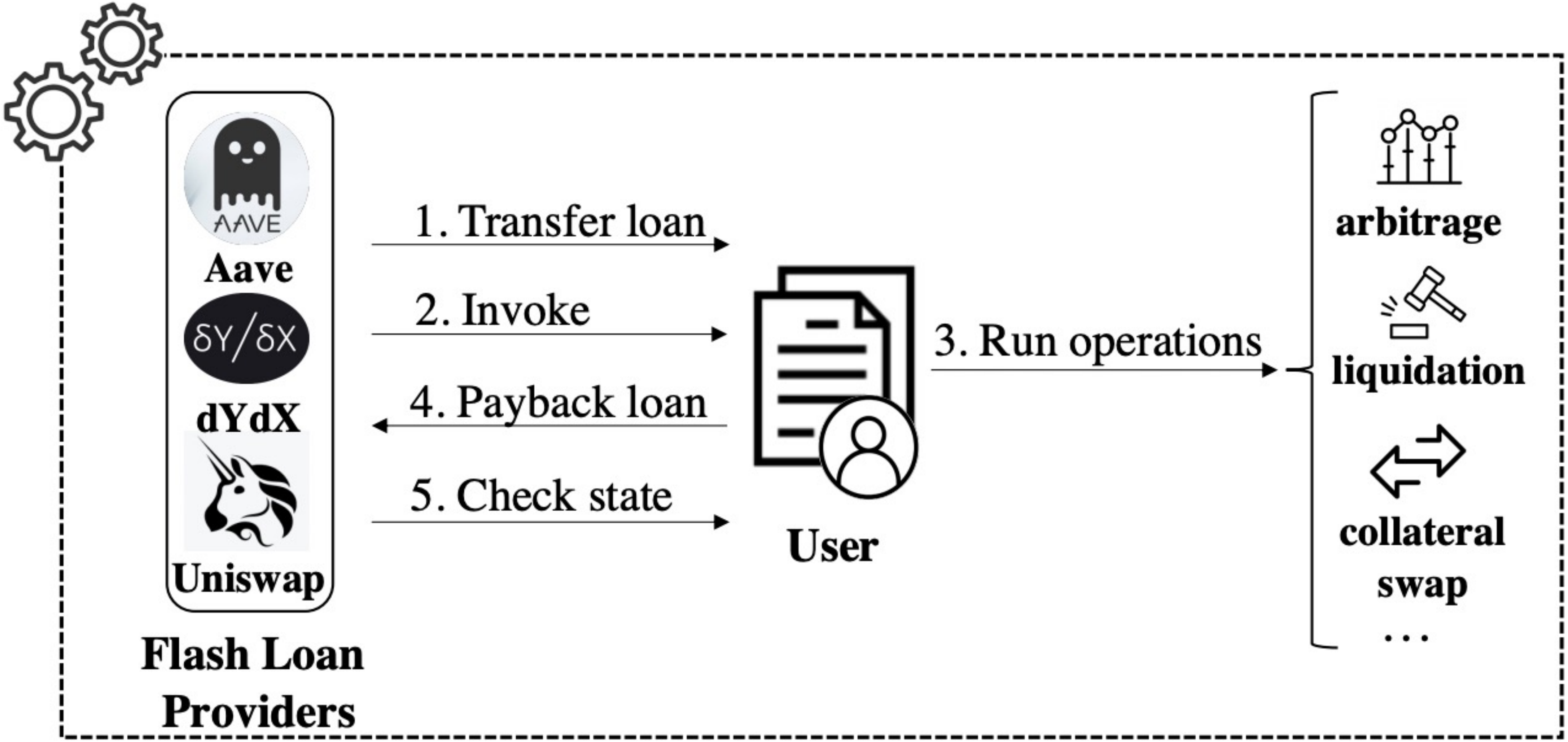
- How stable are stablecoins?
- Domestic and global regulatory and supervisory approaches

Macro-Financial

- Cryptoization, capital flows, and restrictions
- Monetary policy transmission
- Bank disintermediation

Source: Parma Bains, Mohamed Diaby, Dimitris Drakopoulos, Julia Faltermeier, Federico Grinberg, Evan Papageorgiou, Dmitri Petrov, Patrick Schneider, and Nobu Sugimoto (2021), The Crypto Ecosystem and Financial Stability Challenges, International Monetary Fund, October 2021

Decentralized Finance Applications (DApps): Flash Loan Transaction



Source: Wang, Dabao, Siwei Wu, Ziling Lin, Lei Wu, Xingliang Yuan, Yajin Zhou, Haoyu Wang, and Kui Ren (2021). "Towards A First Step to Understand Flash Loan and Its Applications in DeFi Ecosystem." In *Proceedings of the Ninth International Workshop on Security in Blockchain and Cloud Computing*, pp. 23-28. 2021.

The Economics of Money, Banking and Financial Markets

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Economics of Money, Banking and Financial Markets

1. Money, Banking, and Financial System
2. Financial Markets
3. Financial Institutions
4. Central Banking and the Conduct of Monetary Policy
5. International Finance and Monetary Policy
6. Monetary Theory
7. Financial Services Industry

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

INTRODUCTION

1. **Why Study Money, Banking, and Financial Markets?**
2. **An Overview of the Financial System**
3. **What Is Money?**

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

FINANCIAL MARKETS

4. Understanding Interest Rates
5. The Behavior of Interest Rates
6. The Risk and Term Structure of Interest Rates
7. The Stock Market, the Theory of Rational Expectations, and the Efficient Market Hypothesis

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

FINANCIAL INSTITUTIONS

8. An Economic Analysis of Financial Structure

9. Banking and the Management of Financial Institutions

10. Economic Analysis of Financial Regulation

11. Banking Industry: Structure and Competition

12. Financial Crises

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

CENTRAL BANKING AND THE CONDUCT OF MONETARY POLICY

13. Central Banks and the Federal Reserve System

14. The Money Supply Process

15. The Tools of Monetary Policy

16. The Conduct of Monetary Policy: Strategy and Tactics

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

MONETARY THEORY

19. Quantity Theory, Inflation, and the Demand for Money

20. The IS Curve

21. The Monetary Policy and Aggregate Demand Curves

22. Aggregate Demand and Supply Analysis

23. Monetary Policy Theory

24. The Role of Expectations in Monetary Policy

25. Transmission Mechanisms of Monetary Policy

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Financial Services Industry

26. Financial Crises in Emerging Market Economies

27. The ISLM Model

28. Nonbank Finance

29. Financial Derivatives

30. Conflicts of Interest in the Financial Services Industry

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Why Study Money, Banking, and Financial Markets?

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Why Study Money, Banking, and Financial Markets?

- To examine how financial markets such as bond, stock and foreign exchange markets work
- To examine how financial institutions such as banks and insurance companies work
- To examine the role of money in the economy

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Financial Markets

- **Markets in which funds are transferred from people who have an excess of available funds to people who have a shortage of funds**
    - **Bond market**
    - **Stock market**
    - **Foreign exchange market**

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Financial Institutions

- Financial Intermediaries: institutions that borrow funds from people who have saved and make loans to other people:
  - **Banks**: accept deposits and make loans
  - Other Financial Institutions: **insurance companies**, **finance companies**, **pension funds, mutual funds and investment banks**
- **Financial Innovation**: the advent of the information age and e-finance

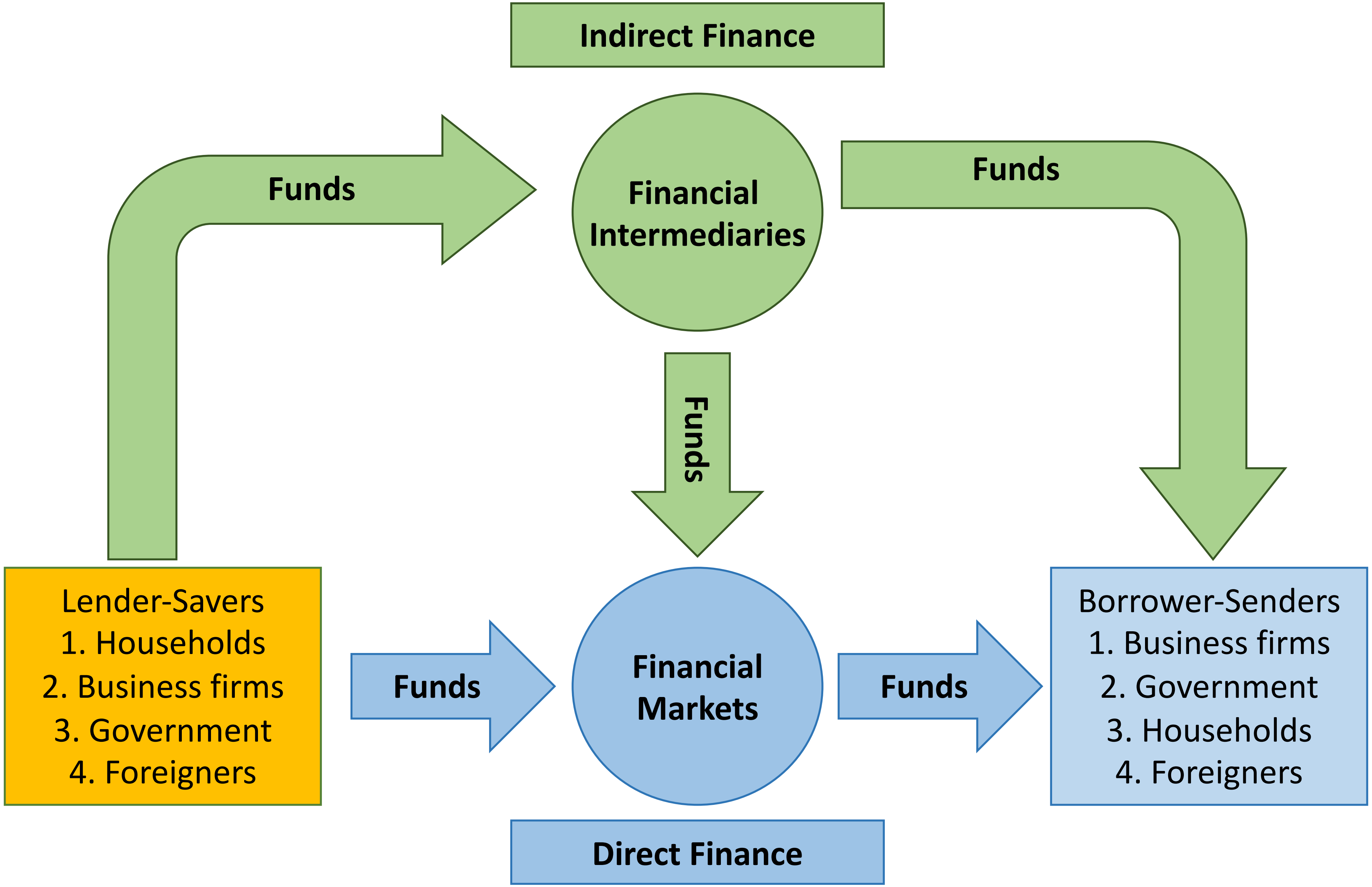
Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Money and Business Cycles

- **Money plays an important role in generating business cycles**
- **Recessions (unemployment) and expansions affect all of us**
- **Monetary Theory ties changes in the money supply to changes in aggregate economic activity and the price level**

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Overview of the Financial System



Indirect Finance

Financial Intermediaries

Funds

Funds

Funds

Lender-Savers
1. Households
2. Business firms
3. Government
4. Foreigners

Funds

Financial Markets

Funds

Borrower-Senders
1. Business firms
2. Government
3. Households
4. Foreigners

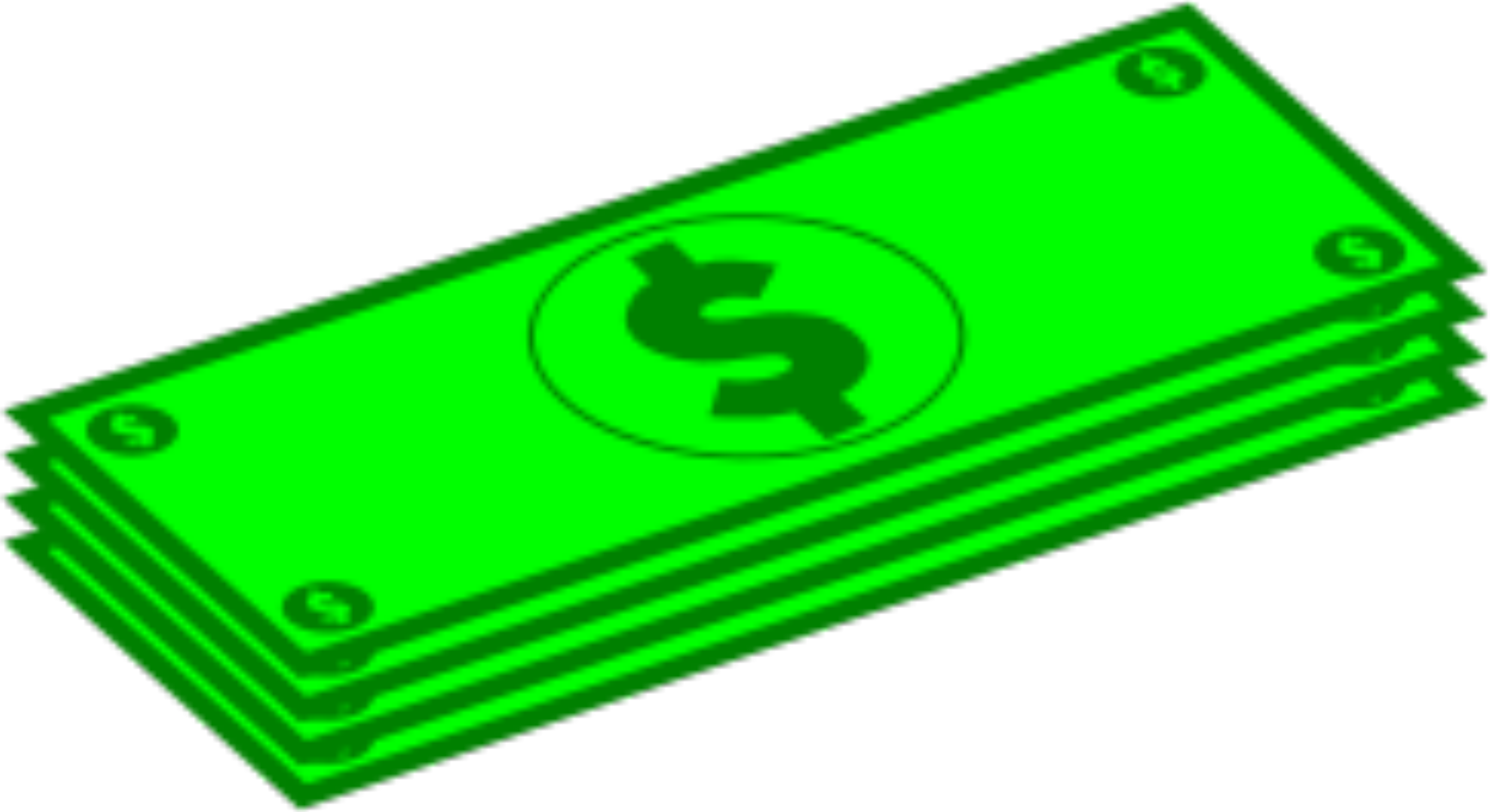
Direct Finance

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

What is Money?

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Money



Source: http://www.wpclipart.com/money/bills/bills_2/stack_of_bills_2.png.html

Bills

Source: http://www.wpclipart.com/money/bills/bills_2/stack_of_bills_2.png.html

Meaning of Money

- **Money (=money supply)** any vehicle used as a means of **exchange** to pay for goods, services or debts.
- In today's society, any **asset** that can quickly be transferred into cash is considered money.
- The more **liquid** an asset is, the closer it is to money.
- In economics, **money** does not mean **wealth** nor does it mean **income**.

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Functions of Money

- Medium of Exchange
- Unit of Account
- Store of Value

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Medium of Exchange

- By eliminating barter, this function of money increases efficiency in a society.
- As human societies started to engage in exchange money had to be invented.
- Any technological change that reduces transaction costs increases the wealth of the society.
- Any technological change that allows people to specialize also increases wealth.

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Unit of Account

- **We use money to measure the value of goods and services.**
- **Suppose we had 4 goods and no money. How do we measure the price of each good?**
  - **A in terms of B**
  - **B in terms of C**
  - **C in terms of D**
  - **A in terms of C**
  - **A in terms of D**
  - **B in terms of D**

N!/2(N-2)!

- **Money allows to quote prices in terms of currency only.**

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Store of Value

- All assets are stored value.
- Money, although without any return, is still desirable to hold because it allows purchases immediately.
- Other assets take time (transaction costs) to use as a payment for purchases.
- The more liquid an asset is, the less transaction cost it carries.
- Inflation erodes the value of money.

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Evolution of the Payments System

- **Commodity Money:**
  - **valuable, easily standardized and divisible commodities (e.g. precious metals, cigarettes).**
- **Fiat Money:**
  - **paper money decreed by governments as legal tender.**

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Electronic Money

- Debit Cards
  - Instant transfer from your checking account to merchant’s checking account.
- Stored Value Card
  - Gift cards.
- Electronic Cash
  - Account set up on a person’s PC from her bank whereby she can buy products over the Internet.
- Electronic Checks
  - Checks written on PC and sent through the Internet.

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Benefits of Paper Checks

- Cheaper than telecommunications network.
- Provide receipts.
- Allow float.
- May be more secure; avoid hacker problems.
- Do not leave a wealth of information trail.

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Measuring Money

- **M1:**
  - **Currency, demand deposits, travelers checks.**
- **M2:**
  - **M1, saving deposits, small time deposits, retail MMMF.**
- **M3:**
  - **M2, large time deposits, repos, Eurodollar deposits, institutional MMMF.**
- **MZM:**
  - **M2, institutional MMMF minus small time deposits.**
- **Growth rates of these aggregates do not always go hand in hand, making monetary policy difficult since signals are conflicting.**

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

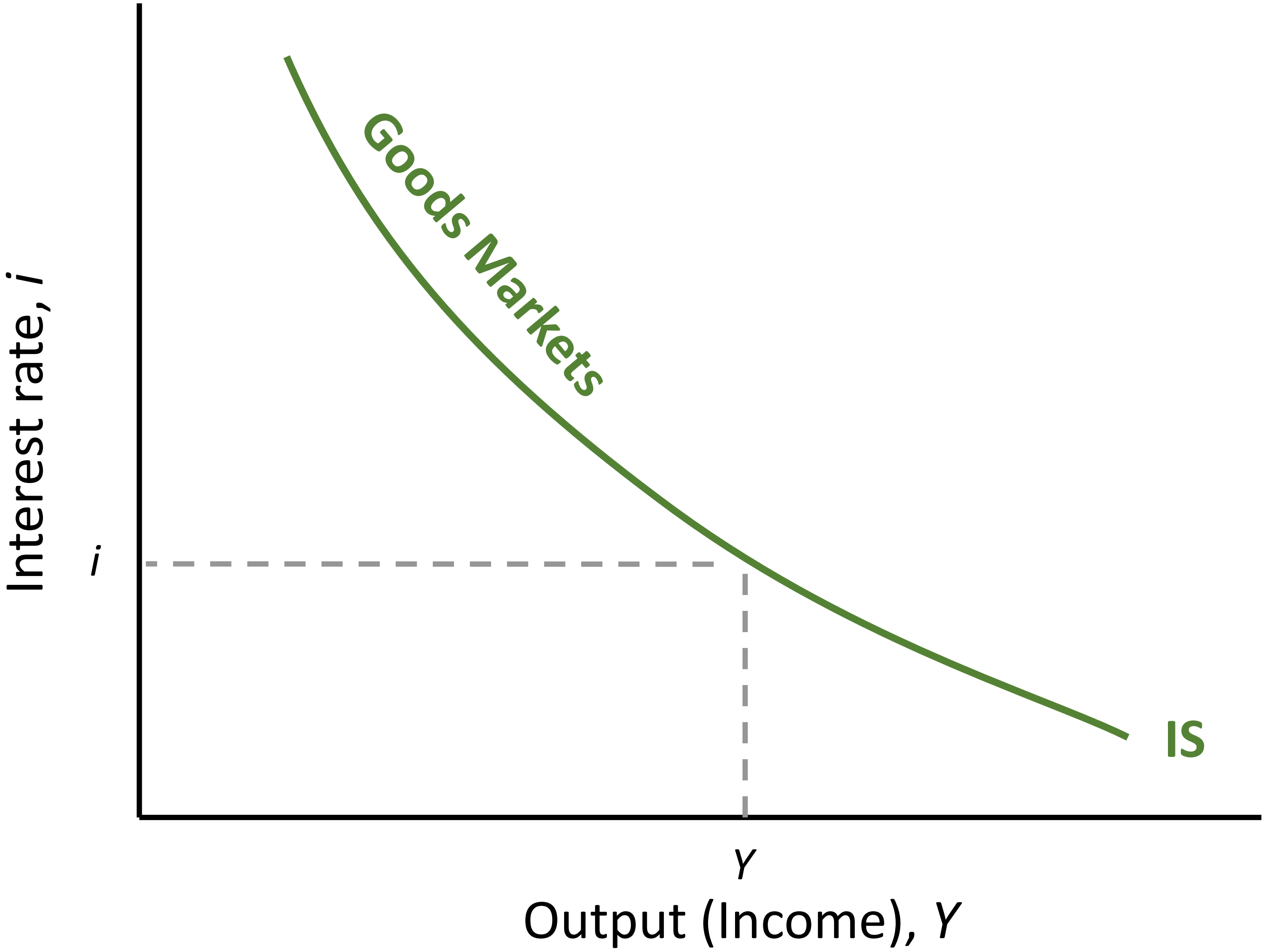
The IS Curve

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

The IS (Investment/Saving) Curve

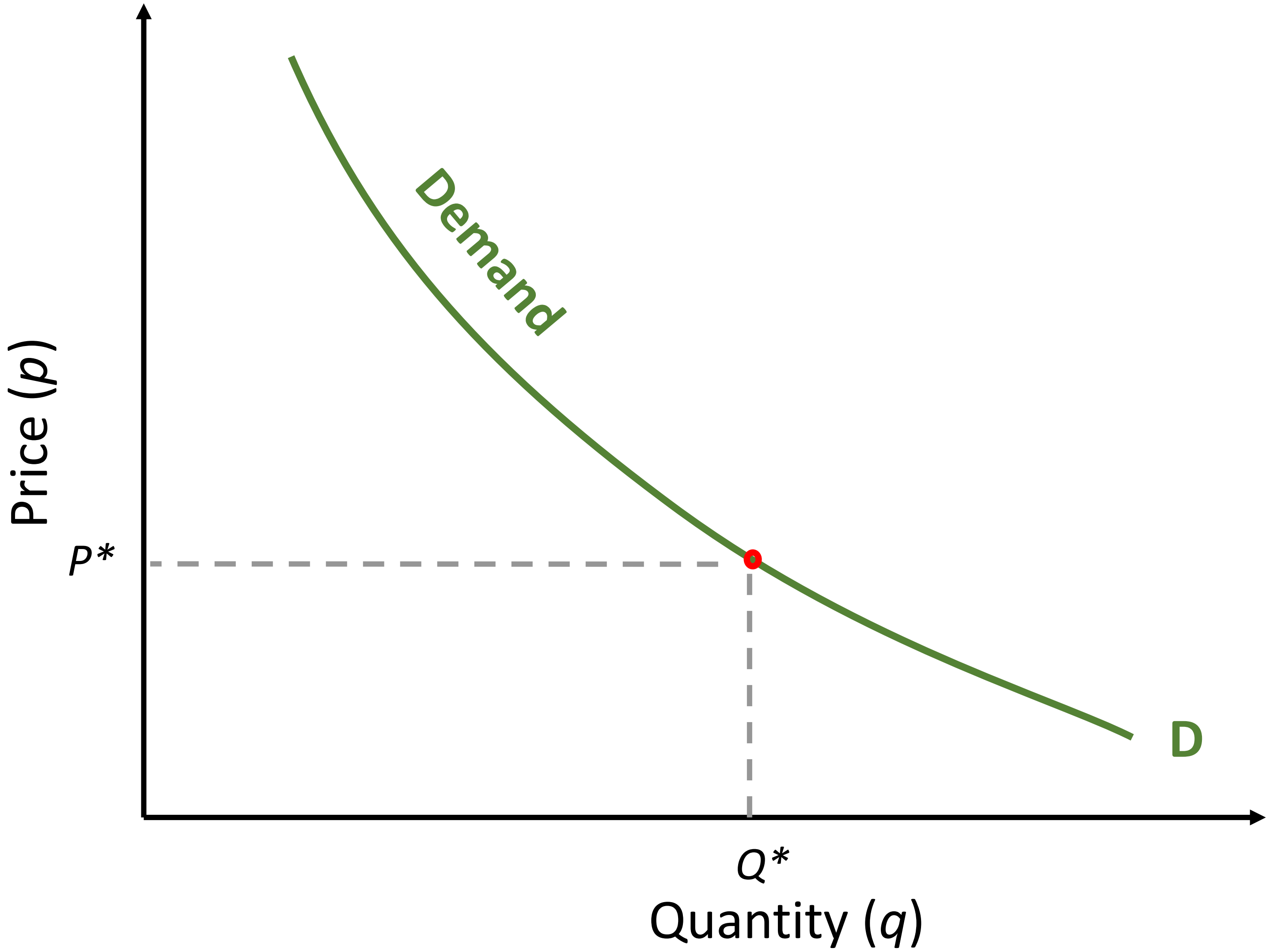
Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

The IS (Investment/Saving) Curve



Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Demand



Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

The ISLM Model

Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

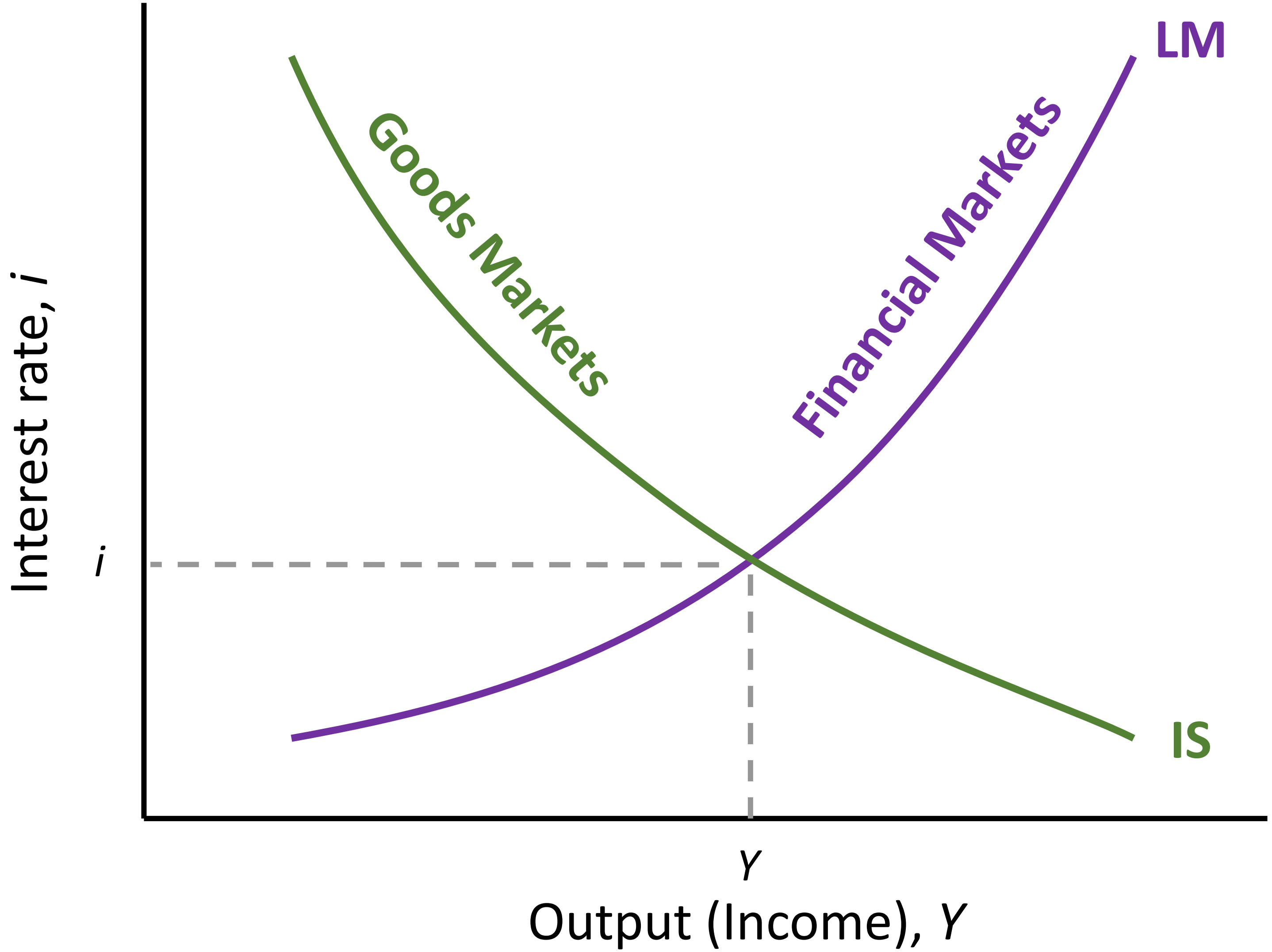
Goods and Financial Markets:

The ISLM Model

(Investment Saving – Liquidity Preference Money Supply) model

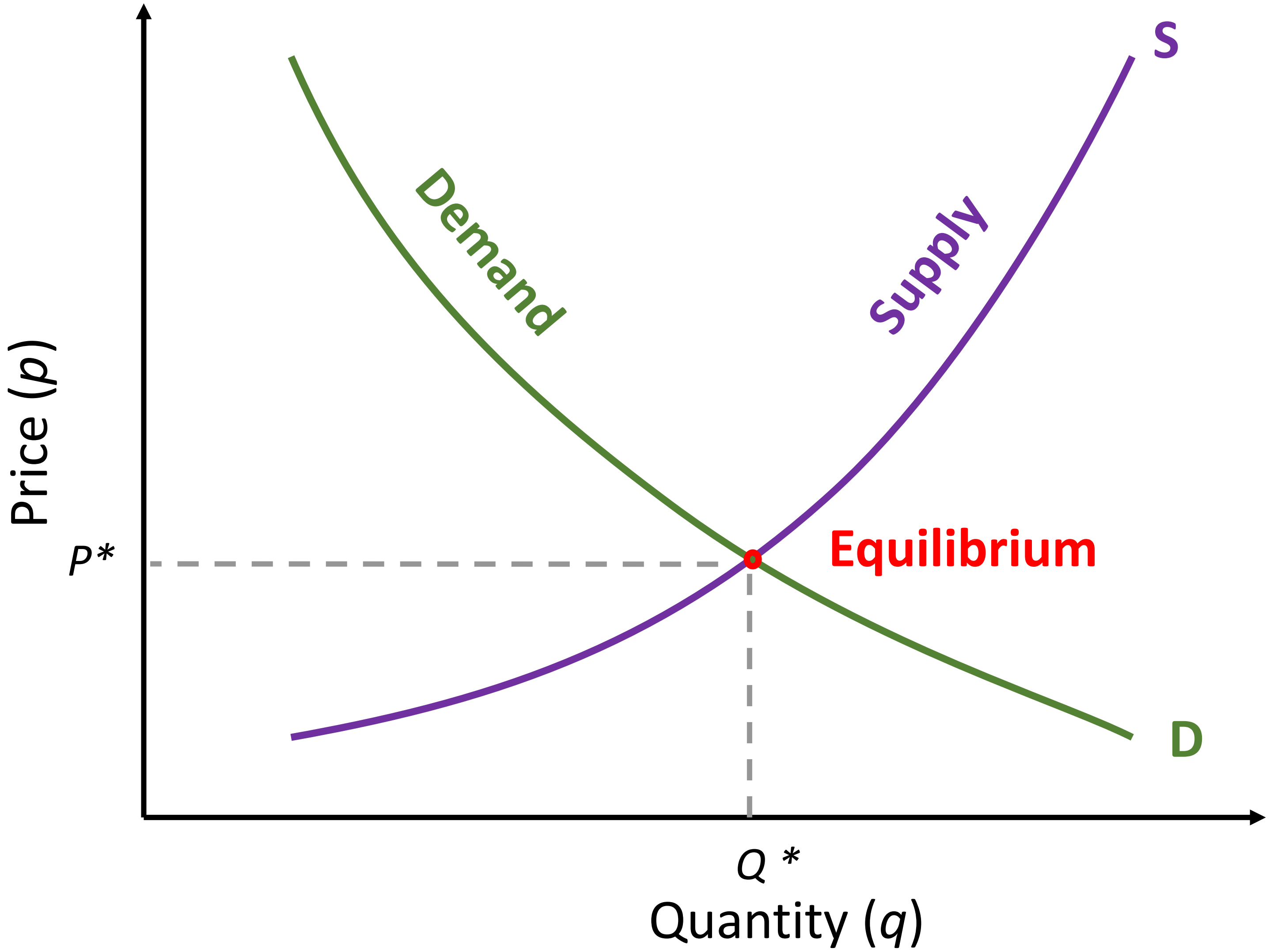
Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

The ISLM Model (Investment Saving – Liquidity Preference Money Supply) model



Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Supply and Demand



Source: Frederic S. Mishkin (2015), The Economics of Money, Banking and Financial Markets, 11th Edition, Pearson

Artificial Intelligence
and
Deep Learning
for
Fintech

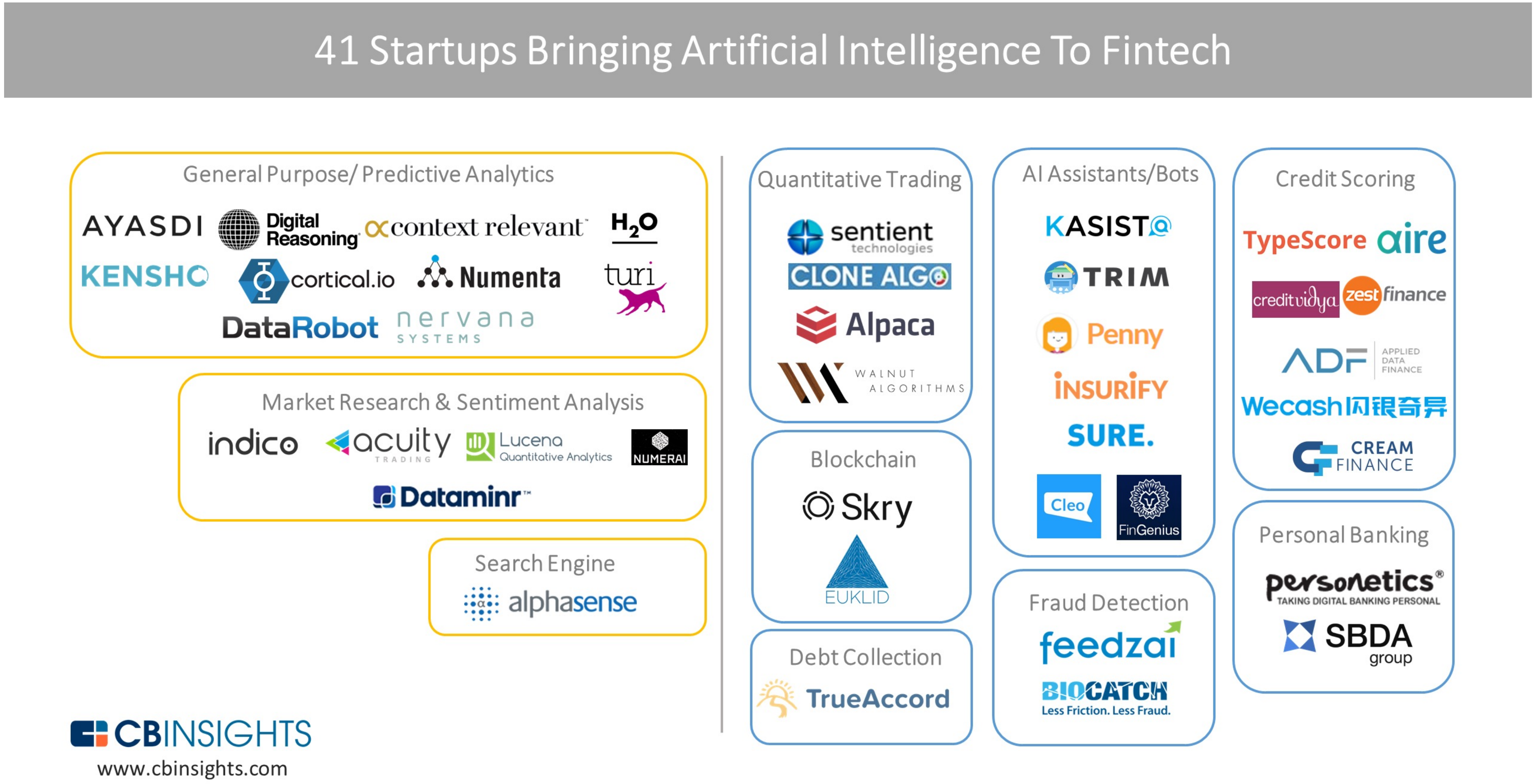
From Algorithmic Trading to Personal Finance Bots: 41 Startups Bringing

AI to Fintech

Source: https://www.cbinsights.com/blog/artificial-intelligence-fintech-market-map-company-list/

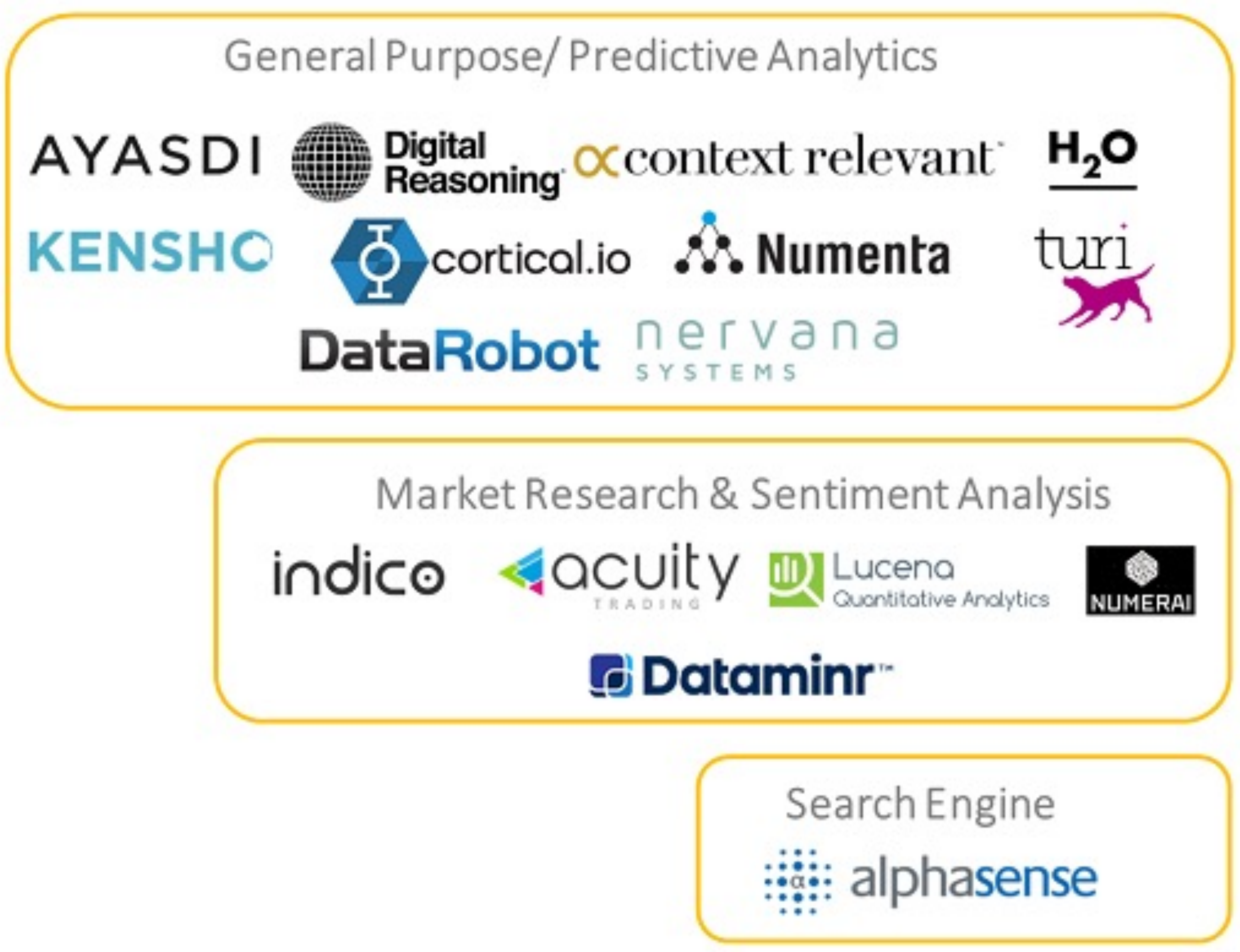
From Algorithmic Trading To Personal Finance Bots: 41 Startups Bringing AI To Fintech

AI in Fintech



Source: https://www.cbinsights.com/blog/artificial-intelligence-fintech-market-map-company-list/

Artificial Intelligence (AI) in Fintech



General Purpose/ Predictive Analytics

- AYASDI
- Digital Reasoning
- context relevant
- H$_2$O
- KENSHO
- cortical.io
- Numenta
- turi
- DataRobot
- nervana systems

Market Research & Sentiment Analysis

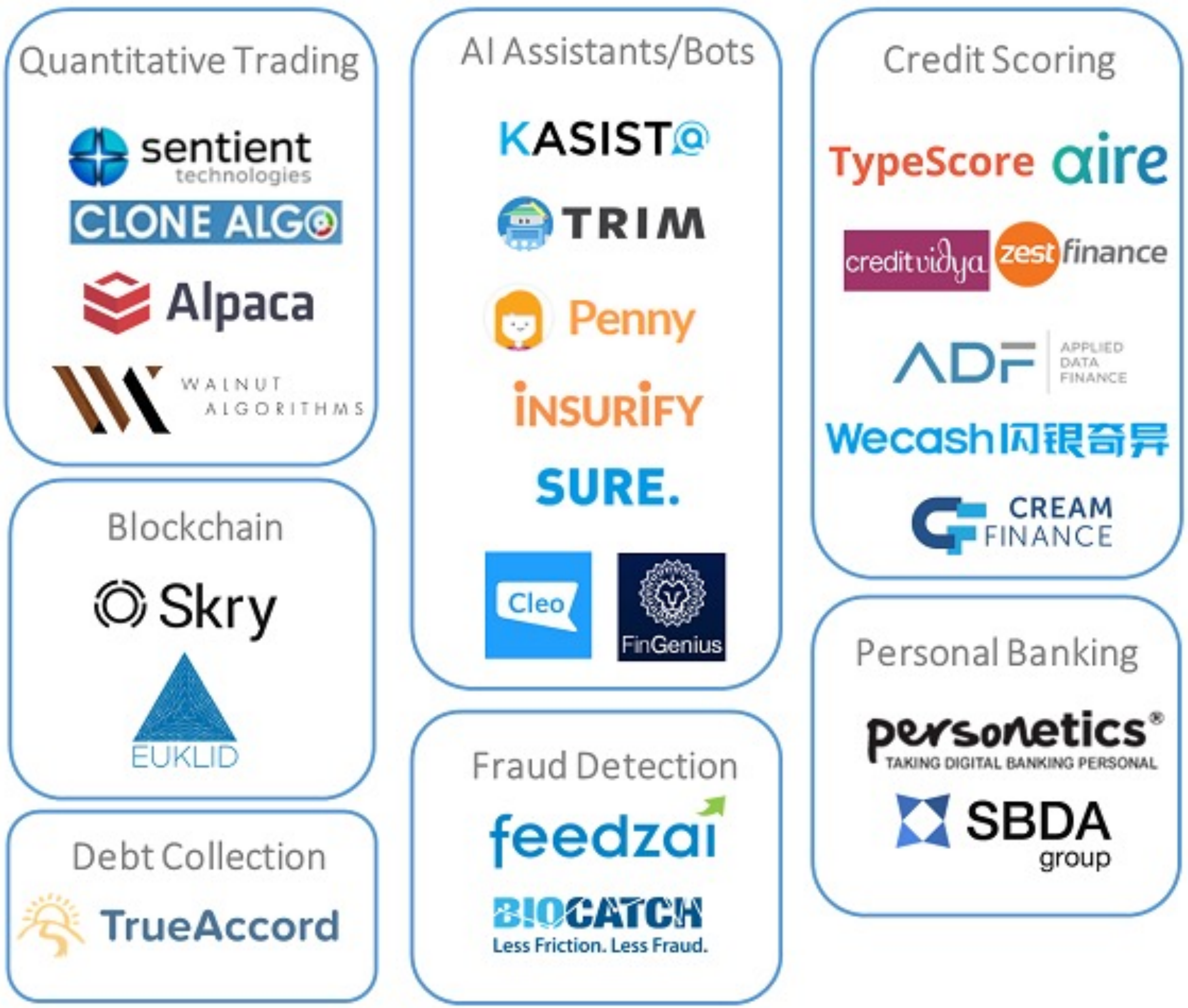
- indico
- acuity trading
- Lucena Quantitative Analytics
- NUMERAI
- Dataminr

Search Engine

- alphasense

Source: https://www.cbinsights.com/blog/artificial-intelligence-fintech-market-map-company-list/

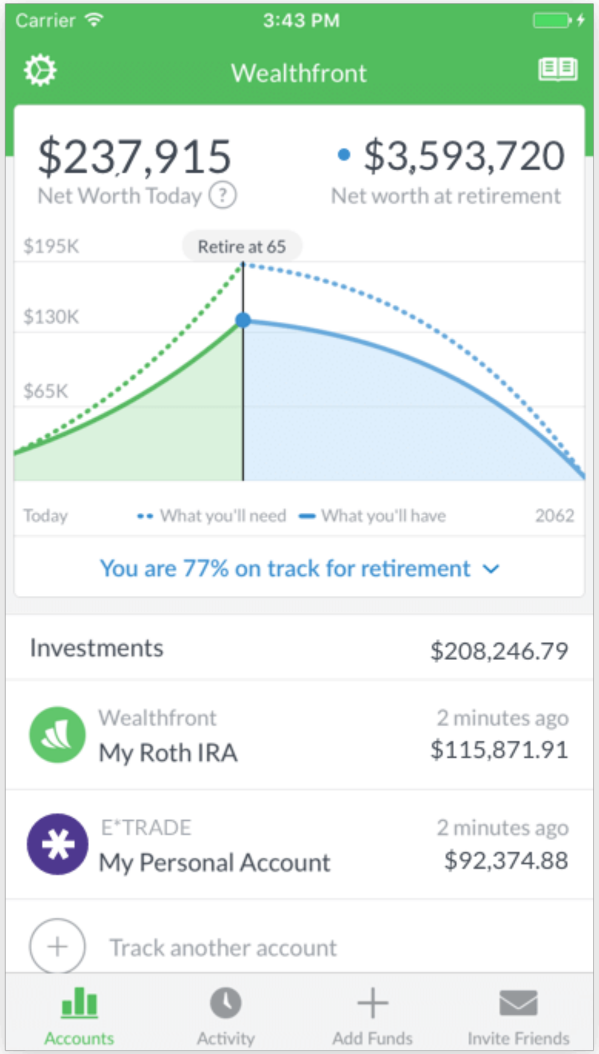
Artificial Intelligence (AI) in Fintech



Source: https://www.cbinsights.com/blog/artificial-intelligence-fintech-market-map-company-list/

wealthfront

Wealthfront Robo Advisor



Wealthfront

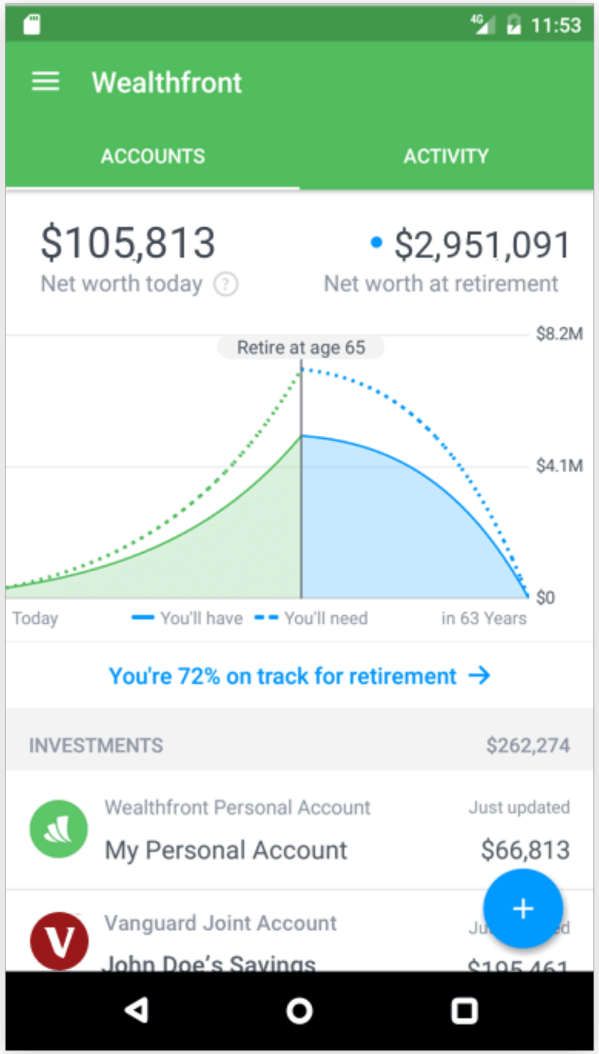
$237,915
Net Worth Today ?

$3,593,720
Net worth at retirement

You are 77% on track for retirement

Investments	$208,246.79
Wealthfront My Roth IRA	2 minutes ago $115,871.91
E*TRADE My Personal Account	2 minutes ago $92,374.88

Track another account



Wealthfront

$105,813
Net worth today ?

$2,951,091
Net worth at retirement

You're 72% on track for retirement →

INVESTMENTS	$262,274
Wealthfront Personal Account My Personal Account	Just updated $66,813
Vanguard Joint Account John Doe's Savings	Ju...d $105,461

Source: https://www.wealthfront.com/

Financial Services

Technology Innovation

Innovation

Source: https://www.merriam-webster.com/dictionary/innovation

Innovation:

a new idea, method, or device

Source: https://www.merriam-webster.com/dictionary/innovation

Innovation:

something

new

Source: https://www.merriam-webster.com/dictionary/innovation

Novelty :

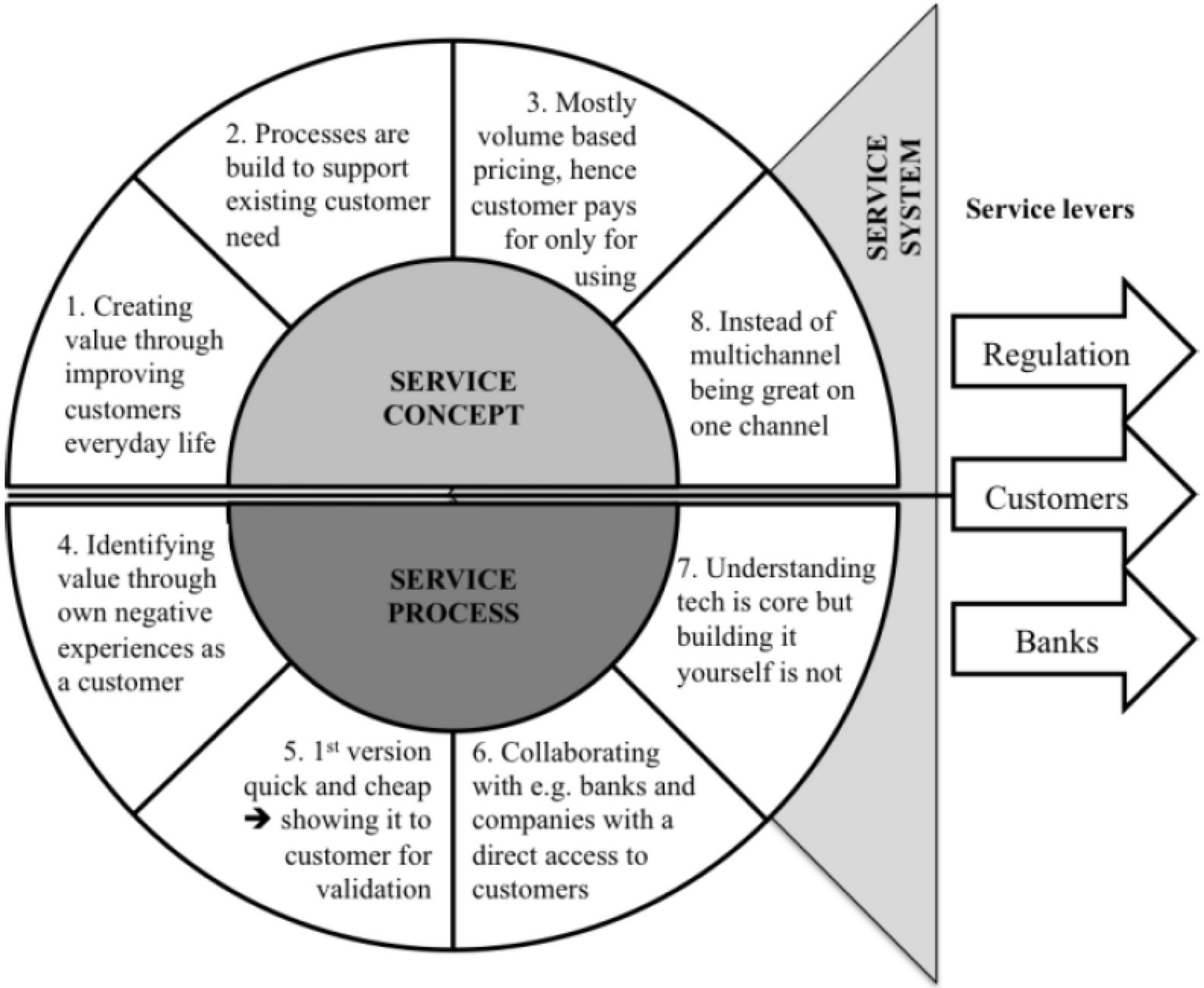
something new or unusual

the novelty of a self-driving car

Source: https://www.merriam-webster.com/dictionary/novelty

Creativity is not a new Idea. Creativity is an old belief you leave behind

FinTechs as Service Innovators: Analysing Components of Innovation



Source: Riikkinen, Mikko, Kaisa Still, Saila Saraniemi, and Katri Kallio. "FinTechs as service innovators: analysing components of innovation." In *ISPIM Innovation Symposium*, The International Society for Professional Innovation Management (ISPIM), 2016.

Innovation

“a process of searching and recombining existing knowledge elements”

Source: Savino, Tommaso, Antonio Messeni Petruzzelli, and Vito Albino. "Search and recombination process to innovate: A review of the empirical evidence and a research agenda." International Journal of Management Reviews (2017).

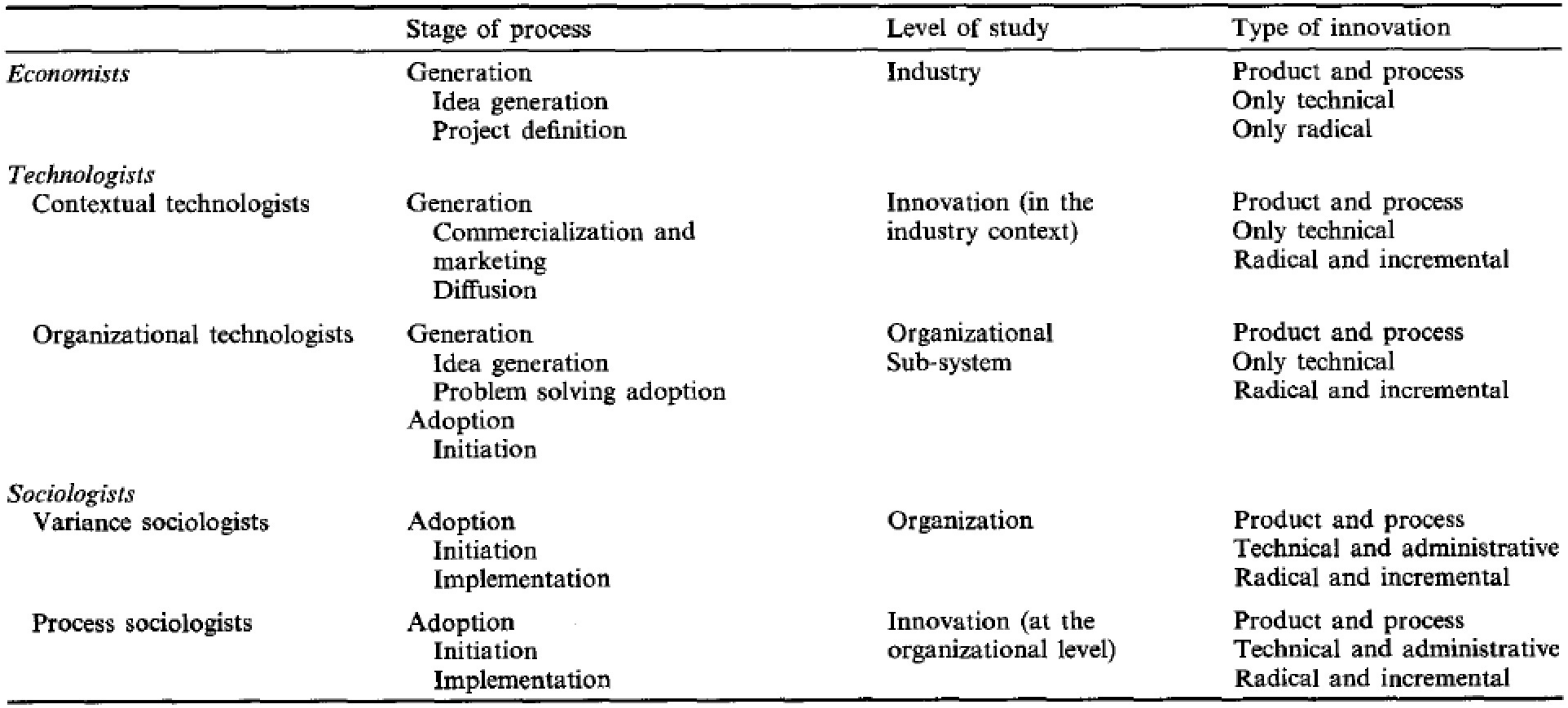
Search and recombination process to innovate: A review of the empirical evidence and a research agenda

Source: Savino, Tommaso, Antonio Messeni Petruzzelli, and Vito Albino. "Search and recombination process to innovate: A review of the empirical evidence and a research agenda." International Journal of Management Reviews (2017).

Innovation Research in Economics, Sociology and Technology Management

Source: Gopalakrishnan, Shanti, and Fariborz Damanpour.
"A review of innovation research in economics, sociology and technology management." *Omega* 25, no. 1 (1997): 15-28.

Innovation Research in Economics, Sociology and Technology Management



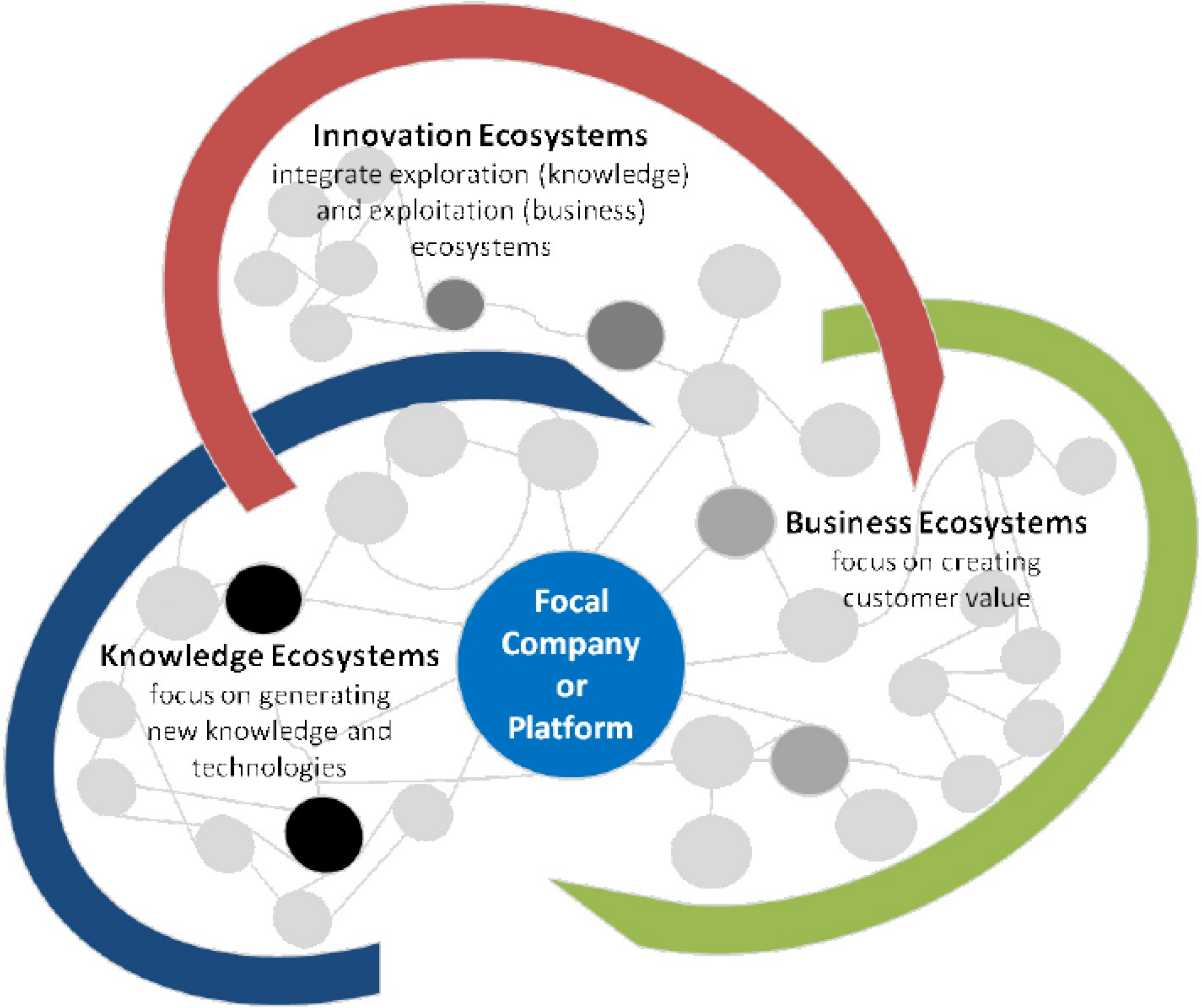
	Stage of process	Level of study	Type of innovation
Economists	Generation Idea generation Project definition	Industry	Product and process Only technical Only radical
Technologists			
Contextual technologists	Generation Commercialization and marketing Diffusion	Innovation (in the industry context)	Product and process Only technical Radical and incremental
Organizational technologists	Generation Idea generation Problem solving adoption Adoption Initiation	Organizational Sub-system	Product and process Only technical Radical and incremental
Sociologists			
Variance sociologists	Adoption Initiation Implementation	Organization	Product and process Technical and administrative Radical and incremental
Process sociologists	Adoption Initiation Implementation	Innovation (at the organizational level)	Product and process Technical and administrative Radical and incremental

Source: Gopalakrishnan, Shanti, and Fariborz Damanpour.
"A review of innovation research in economics, sociology and technology management." *Omega* 25, no. 1 (1997): 15-28.

Business, Innovation, and Knowledge Ecosystems

Source: Valkokari, Katri. "Business, innovation, and knowledge ecosystems: how they differ and how to survive and thrive within them." *Technology Innovation Management Review* 5, no. 8 (2015).

Business, Innovation, and Knowledge Ecosystems



Innovation Ecosystems
integrate exploration (knowledge) and exploitation (business) ecosystems

Business Ecosystems
focus on creating customer value

Knowledge Ecosystems
focus on generating new knowledge and technologies

Focal Company or Platform

Source: Valkokari, Katri. "Business, innovation, and knowledge ecosystems: how they differ and how to survive and thrive within them." *Technology Innovation Management Review* 5, no. 8 (2015).

Innovation Ecosystems Characteristics

	Business Ecosystems	**Innovation Ecosystems**	**Knowledge Ecosystems**
Baseline of Ecosystem	Resource exploitation for customer value	**Co-creation of innovation**	Knowledge exploration
Relationships and Connectivity	Global business relationships both competitive and co-operative	Geographically clustered actors, different levels of collaboration and openness	Decentralized and disturbed knowledge nodes, synergies through knowledge exchange
Actors and Roles	Suppliers, customers, and focal companies as a core, other actors more loosely involved	**Innovation policymakers, local intermediators, innovation brokers, and funding organizations**	Research institutes, innovators, and technology entrepreneurs serve as knowledge nodes
Logic of Action	A main actor that operates as a platform sharing resources, assets, and benefits or aggregates other actors together in the networked business operations	Geographically proximate actors interacting around hubs facilitated by intermediating actors	A large number of actors that are grouped around knowledge exchange or a central non-proprietary resource for the benefit of all actors

Source: Valkokari, Katri. "Business, innovation, and knowledge ecosystems: how they differ and how to survive and thrive within them." *Technology Innovation Management Review* 5, no. 8 (2015).

Diffusion of Innovation Theory

(DOI)

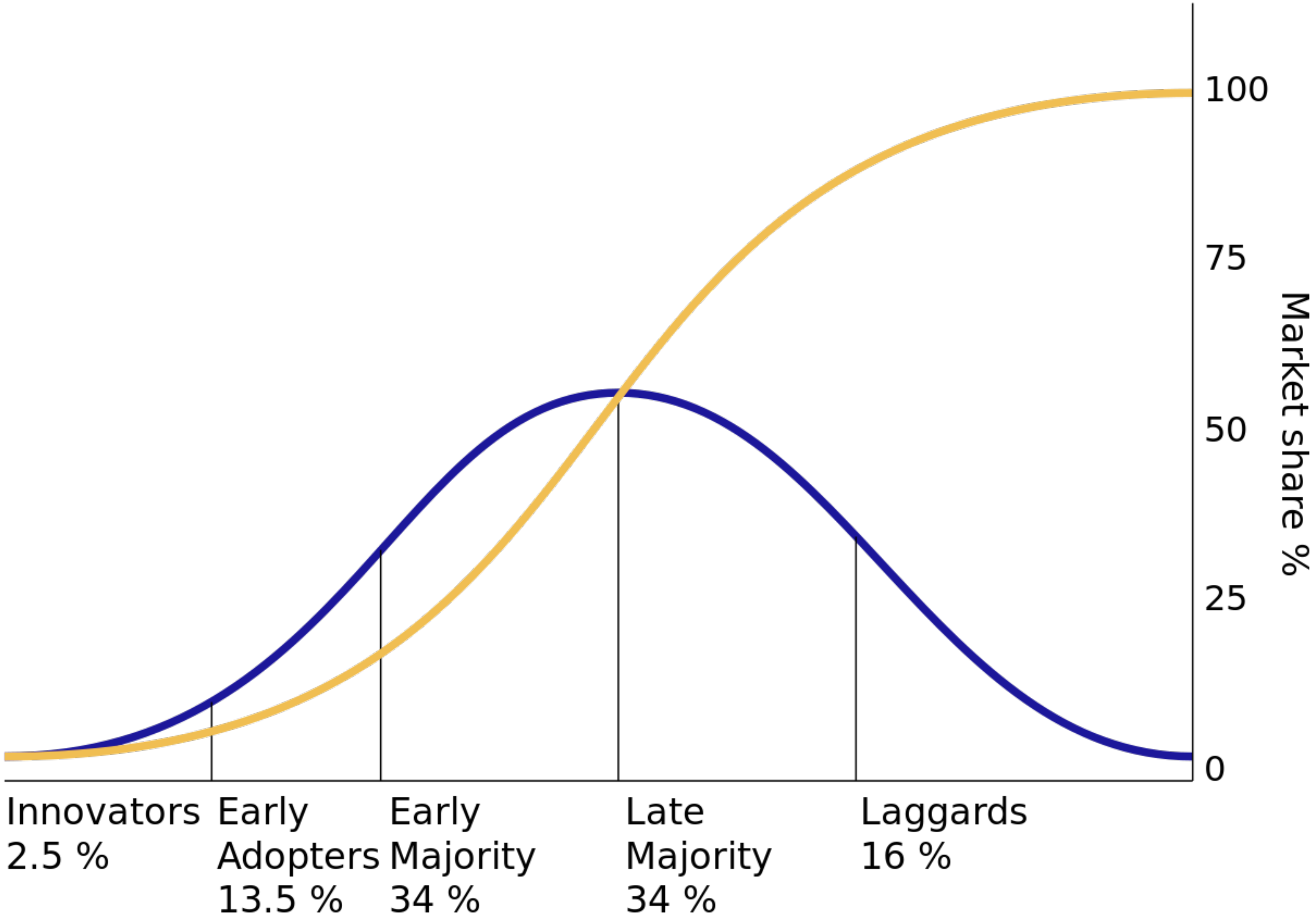
Source: Everett M. Rogers (2003), "Diffusion of Innovations", Free Press, 5th Edition

Innovation
(Diffusion of Innovation)

1. **Relative advantage**
2. **Compatibility**
3. **Complexity**
4. **Trialability**
5. **Observability**

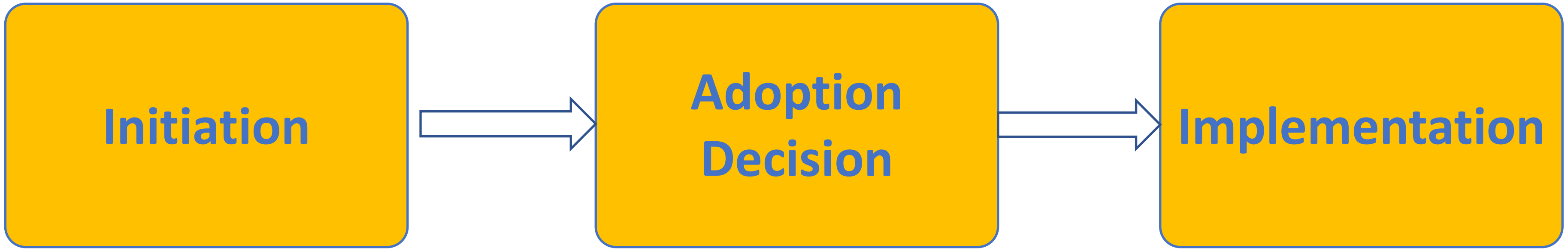
Source: Everett M. Rogers (2003), “Diffusion of Innovations”, Free Press, 5th Edition

Diffusion of Innovation



Source: https://en.wikipedia.org/wiki/Diffusion_of_innovations

Innovation Adoption Process



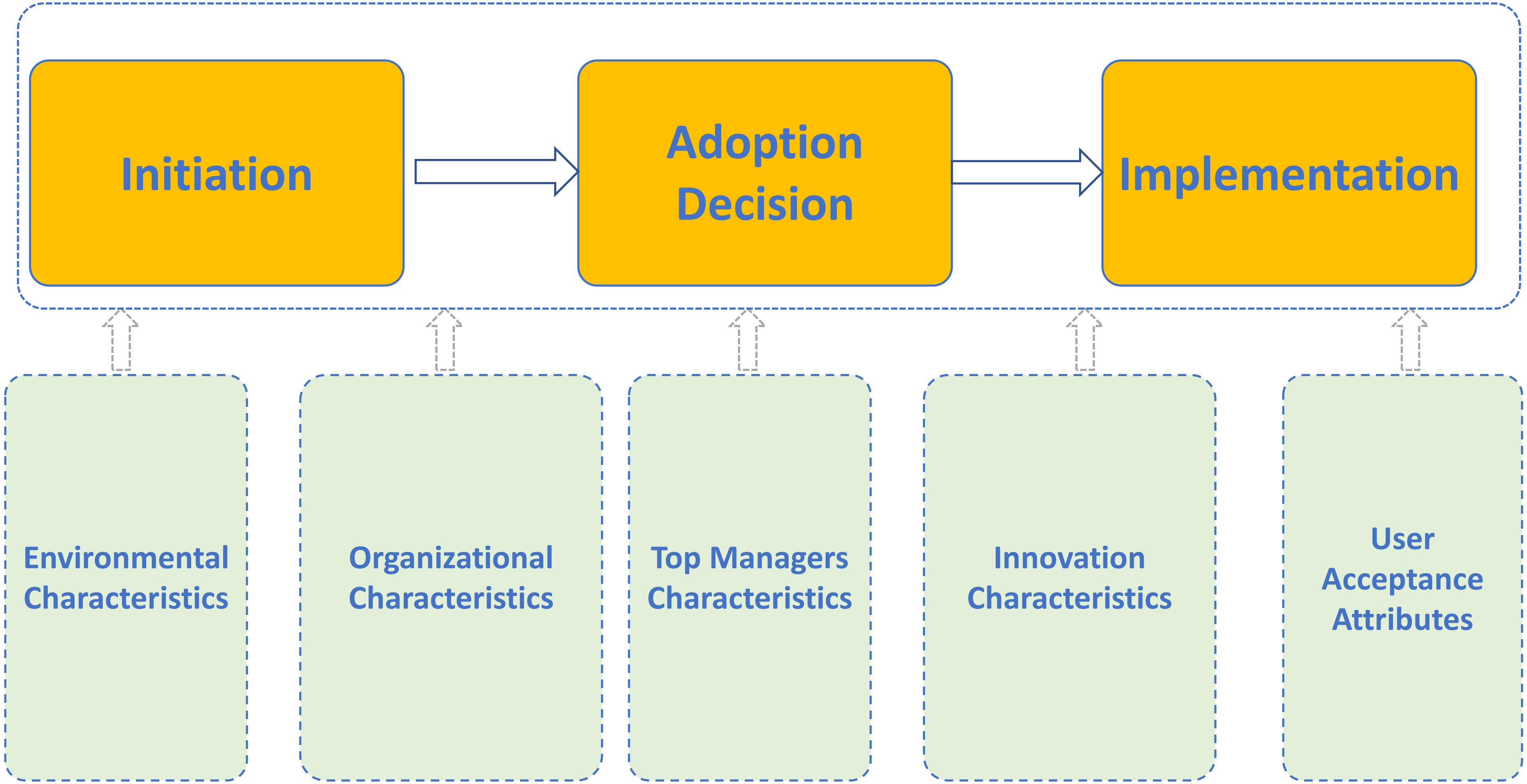
Initiation

Adoption Decision

Implementation

Source: Pichlak, Magdalena.
"The innovation adoption process: A multidimensional approach." Journal of Management and Organization 22, no. 4 (2016): 476.

Innovation Adoption Process



Initiation

Adoption Decision

Implementation

Environmental Characteristics

Organizational Characteristics

Top Managers Characteristics

Innovation Characteristics

User Acceptance Attributes

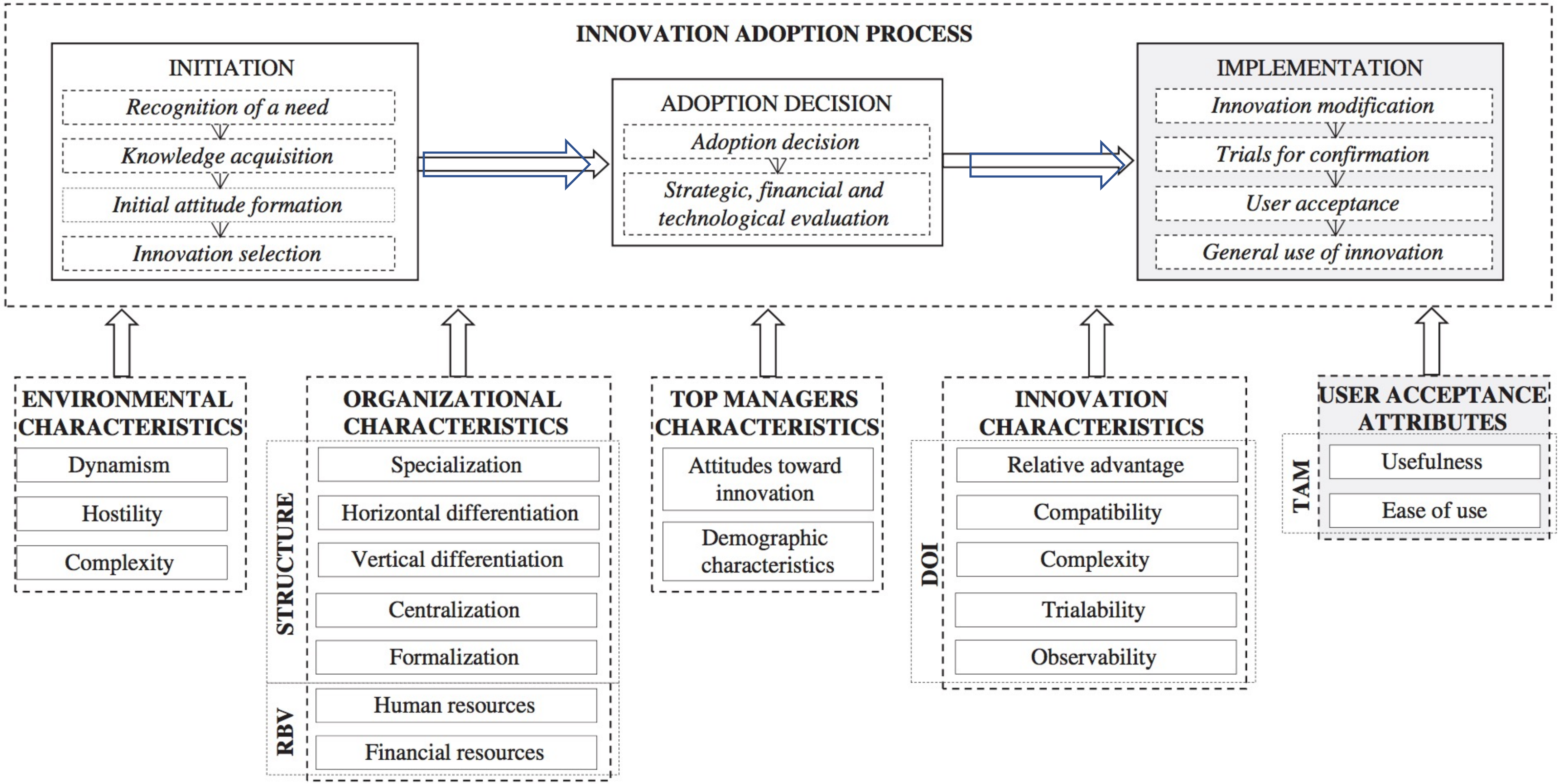
RBV=
Resource-Based View

DOI =
Diffusion of Innovation Theory

TAM=
Technology
Acceptance
Model

Source: Pichlak, Magdalena.
"The innovation adoption process: A multidimensional approach." Journal of Management and Organization 22, no. 4 (2016): 476.

Innovation Adoption Process



INNOVATION ADOPTION PROCESS

INITIATION
- *Recognition of a need*
- *Knowledge acquisition*
- *Initial attitude formation*
- *Innovation selection*

ADOPTION DECISION
- *Adoption decision*
- *Strategic, financial and technological evaluation*

IMPLEMENTATION
- *Innovation modification*
- *Trials for confirmation*
- *User acceptance*
- *General use of innovation*

ENVIRONMENTAL CHARACTERISTICS
- Dynamism
- Hostility
- Complexity

ORGANIZATIONAL CHARACTERISTICS
- **STRUCTURE**
  - Specialization
  - Horizontal differentiation
  - Vertical differentiation
  - Centralization
  - Formalization
- **RBV**
  - Human resources
  - Financial resources

TOP MANAGERS CHARACTERISTICS
- Attitudes toward innovation
- Demographic characteristics

INNOVATION CHARACTERISTICS
- **DOI**
  - Relative advantage
  - Compatibility
  - Complexity
  - Trialability
  - Observability

USER ACCEPTANCE ATTRIBUTES
- **TAM**
  - Usefulness
  - Ease of use

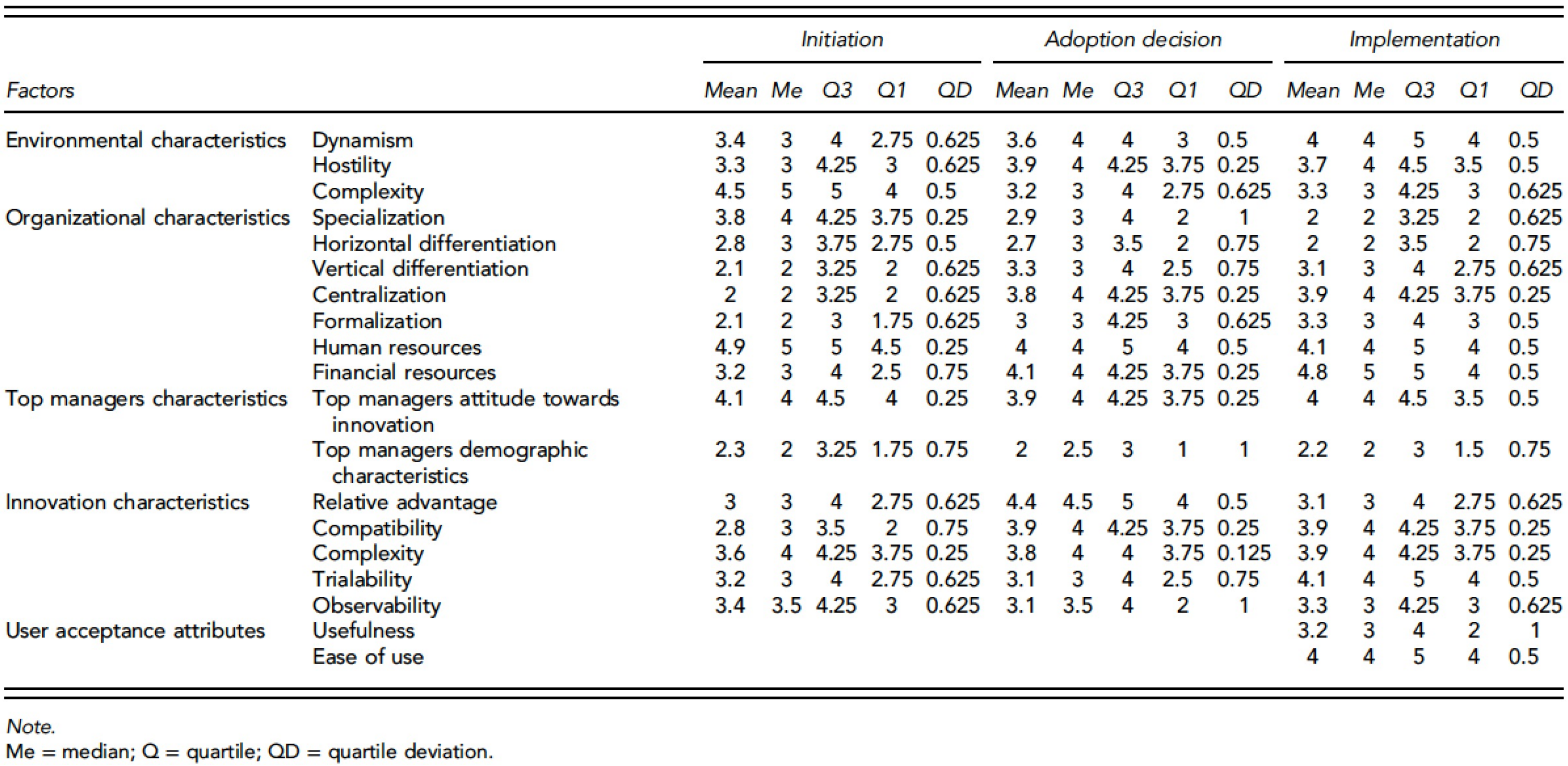
RBV=
Resource-Based View

DOI =
Diffusion of Innovation Theory

TAM=
Technology
Acceptance
Model

Source: Pichlak, Magdalena.
"The innovation adoption process: A multidimensional approach." Journal of Management and Organization 22, no. 4 (2016): 476.

Innovation Adoption Process

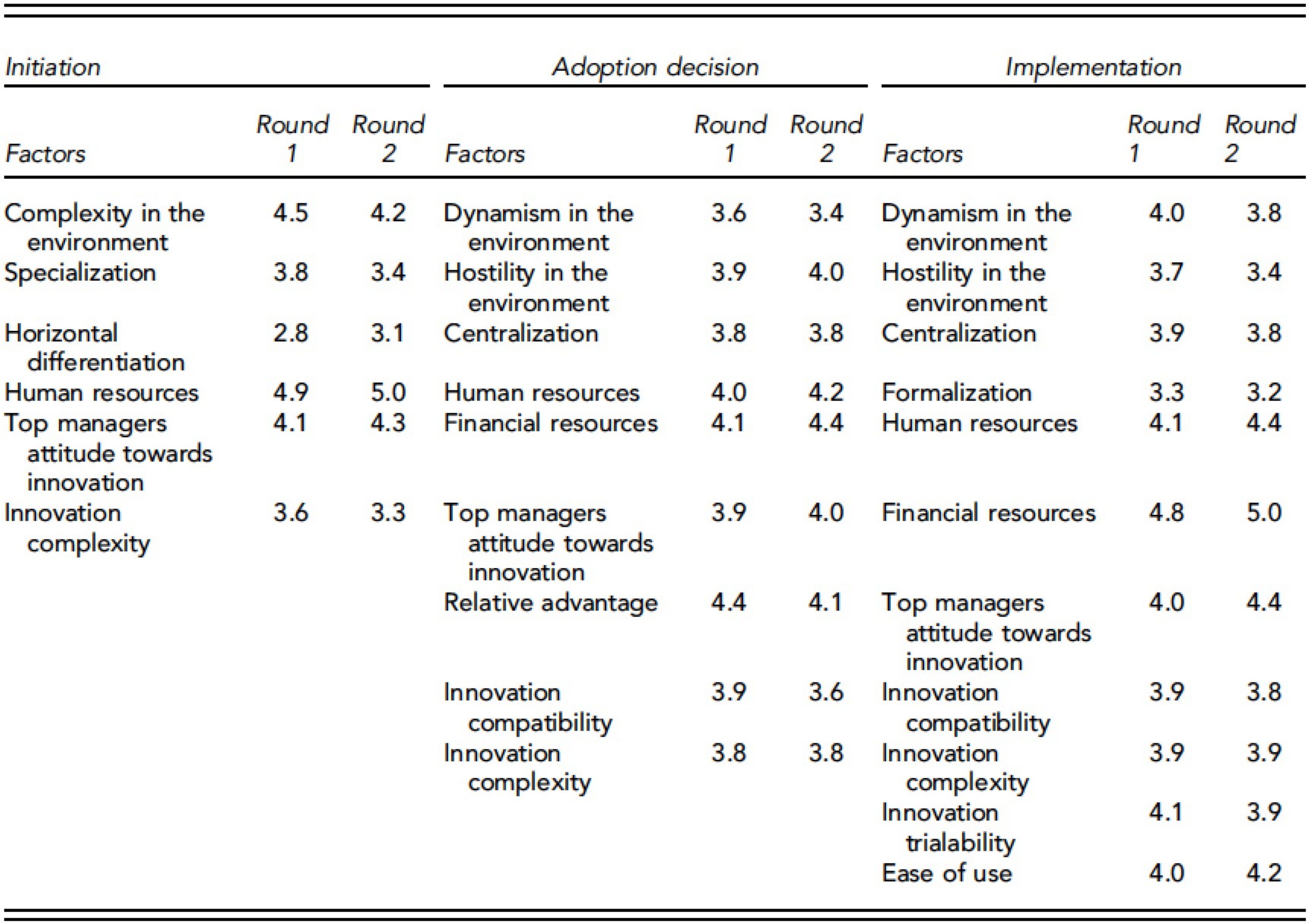


Factors		Initiation					Adoption decision					Implementation				
		Mean	Me	Q3	Q1	QD	Mean	Me	Q3	Q1	QD	Mean	Me	Q3	Q1	QD
Environmental characteristics	Dynamism	3.4	3	4	2.75	0.625	3.6	4	4	3	0.5	4	4	5	4	0.5
	Hostility	3.3	3	4.25	3	0.625	3.9	4	4.25	3.75	0.25	3.7	4	4.5	3.5	0.5
	Complexity	4.5	5	5	4	0.5	3.2	3	4	2.75	0.625	3.3	3	4.25	3	0.625
Organizational characteristics	Specialization	3.8	4	4.25	3.75	0.25	2.9	3	4	2	1	2	2	3.25	2	0.625
	Horizontal differentiation	2.8	3	3.75	2.75	0.5	2.7	3	3.5	2	0.75	2	2	3.5	2	0.75
	Vertical differentiation	2.1	2	3.25	2	0.625	3.3	3	4	2.5	0.75	3.1	3	4	2.75	0.625
	Centralization	2	2	3.25	2	0.625	3.8	4	4.25	3.75	0.25	3.9	4	4.25	3.75	0.25
	Formalization	2.1	2	3	1.75	0.625	3	3	4.25	3	0.625	3.3	3	4	3	0.5
	Human resources	4.9	5	5	4.5	0.25	4	4	5	4	0.5	4.1	4	5	4	0.5
	Financial resources	3.2	3	4	2.5	0.75	4.1	4	4.25	3.75	0.25	4.8	5	5	4	0.5
Top managers characteristics	Top managers attitude towards innovation	4.1	4	4.5	4	0.25	3.9	4	4.25	3.75	0.25	4	4	4.5	3.5	0.5
	Top managers demographic characteristics	2.3	2	3.25	1.75	0.75	2	2.5	3	1	1	2.2	2	3	1.5	0.75
Innovation characteristics	Relative advantage	3	3	4	2.75	0.625	4.4	4.5	5	4	0.5	3.1	3	4	2.75	0.625
	Compatibility	2.8	3	3.5	2	0.75	3.9	4	4.25	3.75	0.25	3.9	4	4.25	3.75	0.25
	Complexity	3.6	4	4.25	3.75	0.25	3.8	4	4	3.75	0.125	3.9	4	4.25	3.75	0.25
	Trialability	3.2	3	4	2.75	0.625	3.1	3	4	2.5	0.75	4.1	4	5	4	0.5
	Observability	3.4	3.5	4.25	3	0.625	3.1	3.5	4	2	1	3.3	3	4.25	3	0.625
User acceptance attributes	Usefulness											3.2	3	4	2	1
	Ease of use											4	4	5	4	0.5

Note.
Me = median; Q = quartile; QD = quartile deviation.

Source: Pichlak, Magdalena.
"The innovation adoption process: A multidimensional approach." Journal of Management and Organization 22, no. 4 (2016): 476.

Innovation Adoption Process

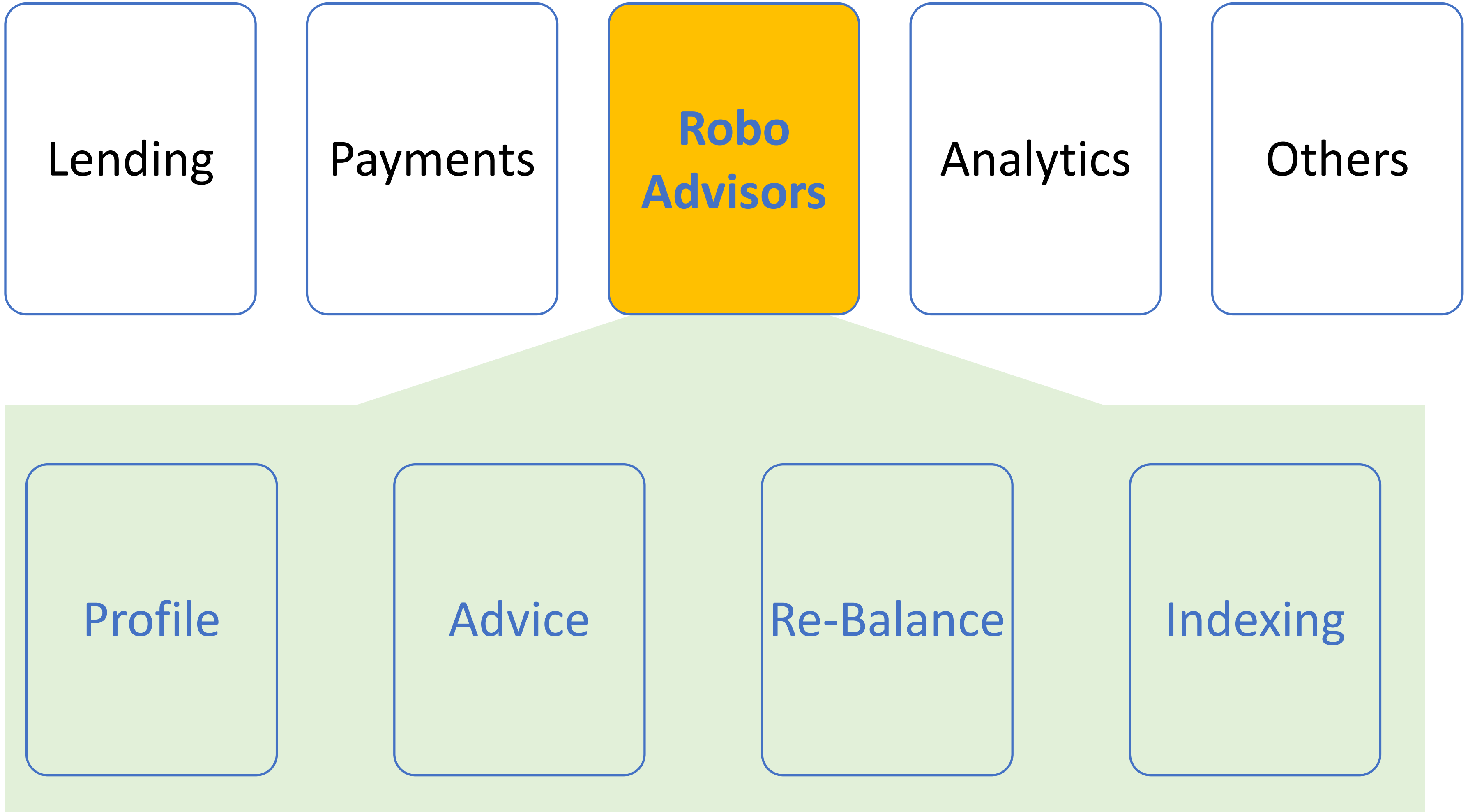


Initiation			*Adoption decision*			*Implementation*		
Factors	*Round 1*	*Round 2*	*Factors*	*Round 1*	*Round 2*	*Factors*	*Round 1*	*Round 2*
Complexity in the environment	4.5	4.2	Dynamism in the environment	3.6	3.4	Dynamism in the environment	4.0	3.8
Specialization	3.8	3.4	Hostility in the environment	3.9	4.0	Hostility in the environment	3.7	3.4
Horizontal differentiation	2.8	3.1	Centralization	3.8	3.8	Centralization	3.9	3.8
Human resources	4.9	5.0	Human resources	4.0	4.2	Formalization	3.3	3.2
Top managers attitude towards innovation	4.1	4.3	Financial resources	4.1	4.4	Human resources	4.1	4.4
Innovation complexity	3.6	3.3	Top managers attitude towards innovation	3.9	4.0	Financial resources	4.8	5.0
			Relative advantage	4.4	4.1	Top managers attitude towards innovation	4.0	4.4
			Innovation compatibility	3.9	3.6	Innovation compatibility	3.9	3.8
			Innovation complexity	3.8	3.8	Innovation complexity	3.9	3.9
						Innovation trialability	4.1	3.9
						Ease of use	4.0	4.2

Source: Pichlak, Magdalena.
"The innovation adoption process: A multidimensional approach." Journal of Management and Organization 22, no. 4 (2016): 476.

FinTech Innovation

FinTech high-level classification



Lending

Payments

Robo Advisors

Analytics

Others

Profile

Advice

Re-Balance

Indexing

Source: Paolo Sironi (2016), “FinTech Innovation: From Robo-Advisors to Goal Based Investing and Gamification”, Wiley.

**“In the next 10 years,
we'll see more
disruption and changes
to the banking and
financial industry
than we've seen in the
preceding 100 years.”**

(Brett King, 2014)

Source: Brett King (2014), Breaking Banks: The Innovators, Rogues, and Strategists Rebooting Banking, Wiley

Fintech: Financial Technology

Disrupting Banking:
The Fintech Startups
That Are Unbundling
Wells Fargo, Citi and
Bank of America

Source: https://www.cbinsights.com/blog/industry-market-map-landscape/

Fintech: Unbunding the Bank

Source: https://www.cbinsights.com/blog/disrupting-banking-fintech-startups-2016/

Fintech: Unbunding the Bank

Wealth Management: Wealthfront

Source: https://www.cbinsights.com/blog/disrupting-banking-fintech-startups-2016/

Fintech: Financial Technology

Disrupting European Banking: The FinTech Startups That Are Unbundling HSBC, Santander, and BNP

Source: https://www.cbinsights.com/blog/industry-market-map-landscape/

Unbundling of a European Bank

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Source: https://www.cbinsights.com/blog/disrupting-european-banking-fintech-startups/

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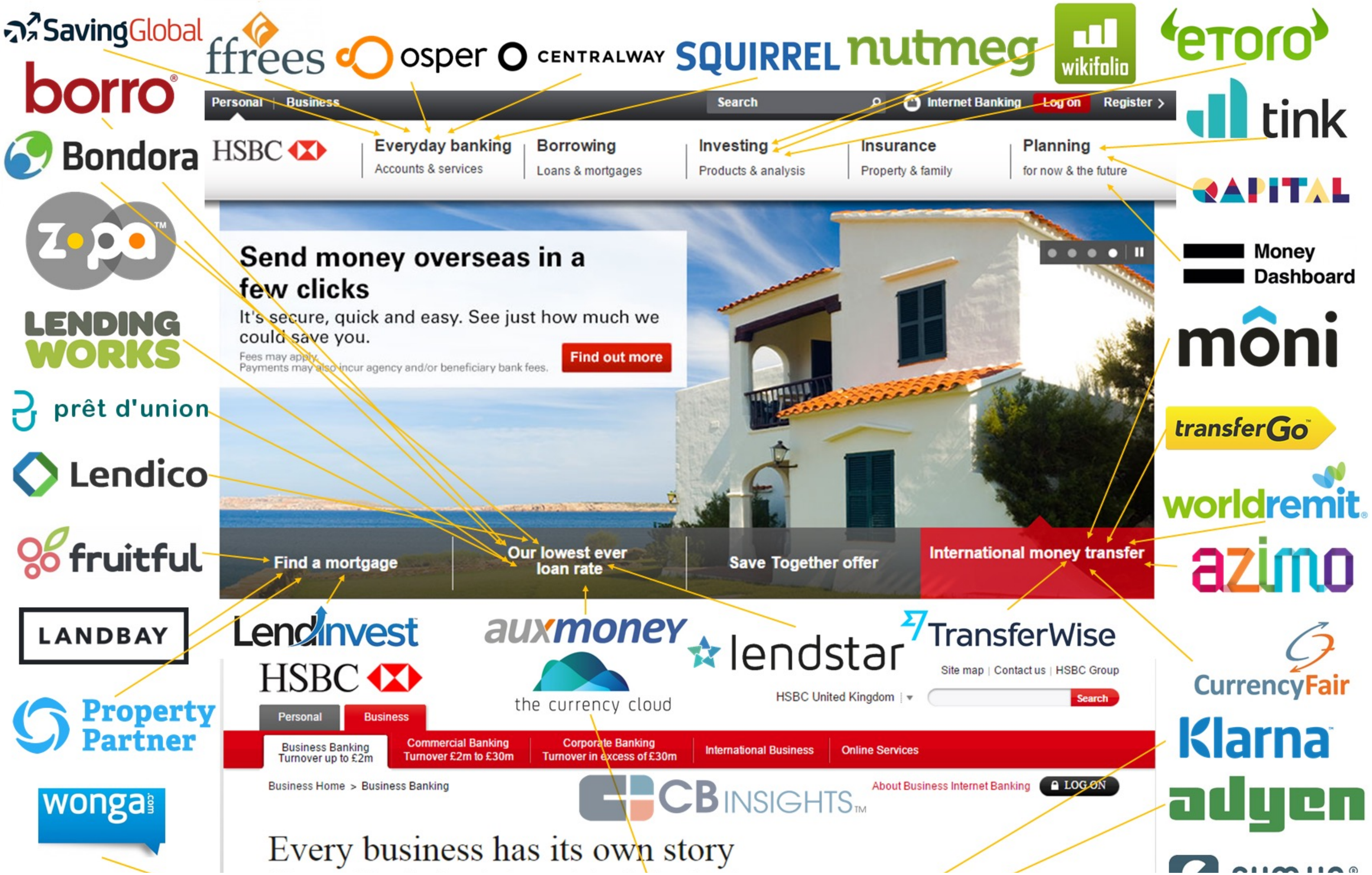

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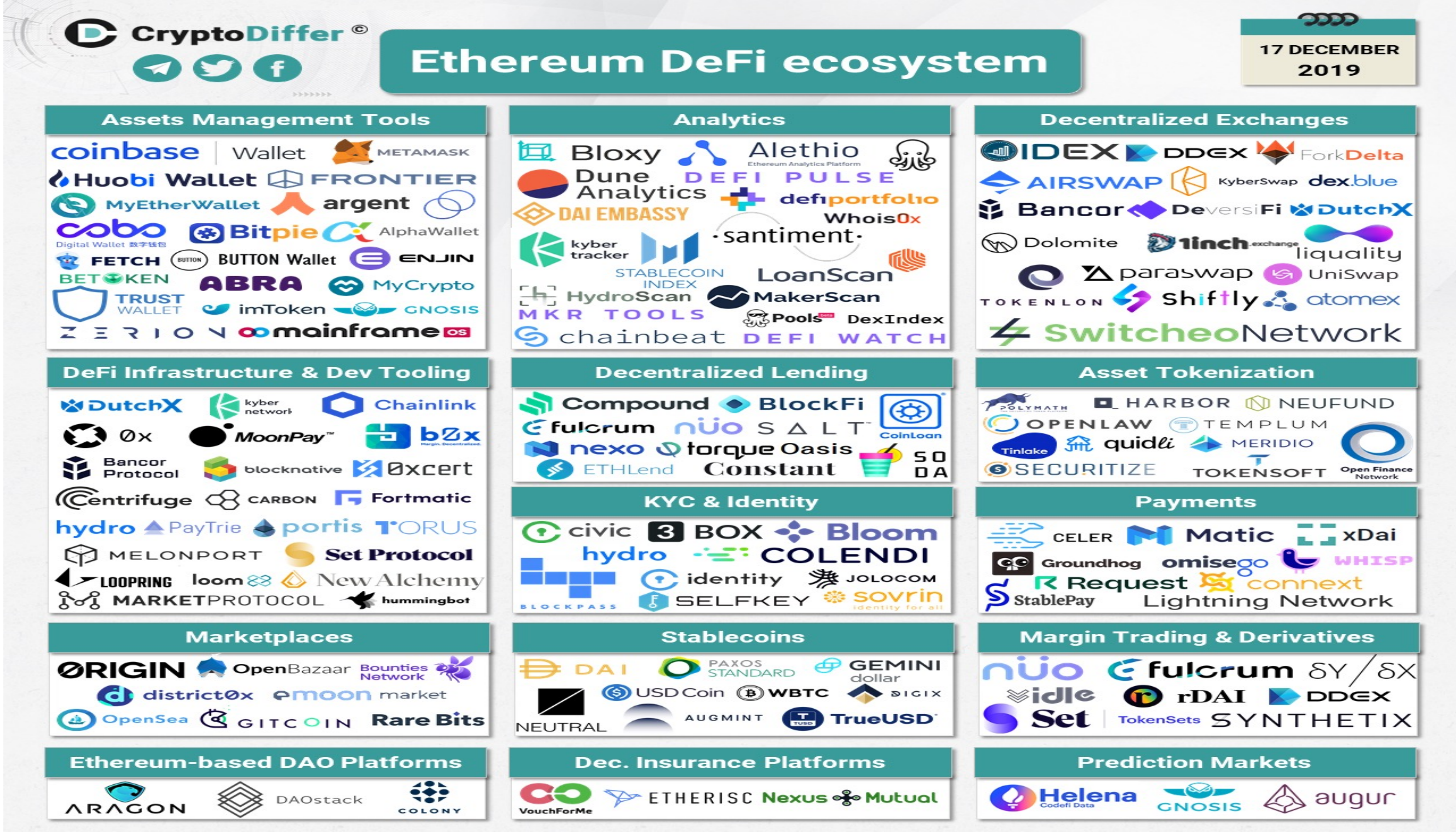
Source: https://www.cbinsights.com/blog/disrupting-european-banking-fintech-startups/

Financial Technology (Fintech) Categories

1. Banking Infrastructure
2. Business Lending
3. Consumer and Commercial Banking
4. Consumer Lending
5. Consumer Payments
6. Crowdfunding
7. Equity Financing
8. Financial Research and Data
9. Financial Transaction Security
10. Institutional Investing
11. International Money Transfer
12. Payments Backend and Infrastructure
13. Personal Finance
14. Point of Sale Payments
15. Retail Investing
16. Small and Medium Business Tools

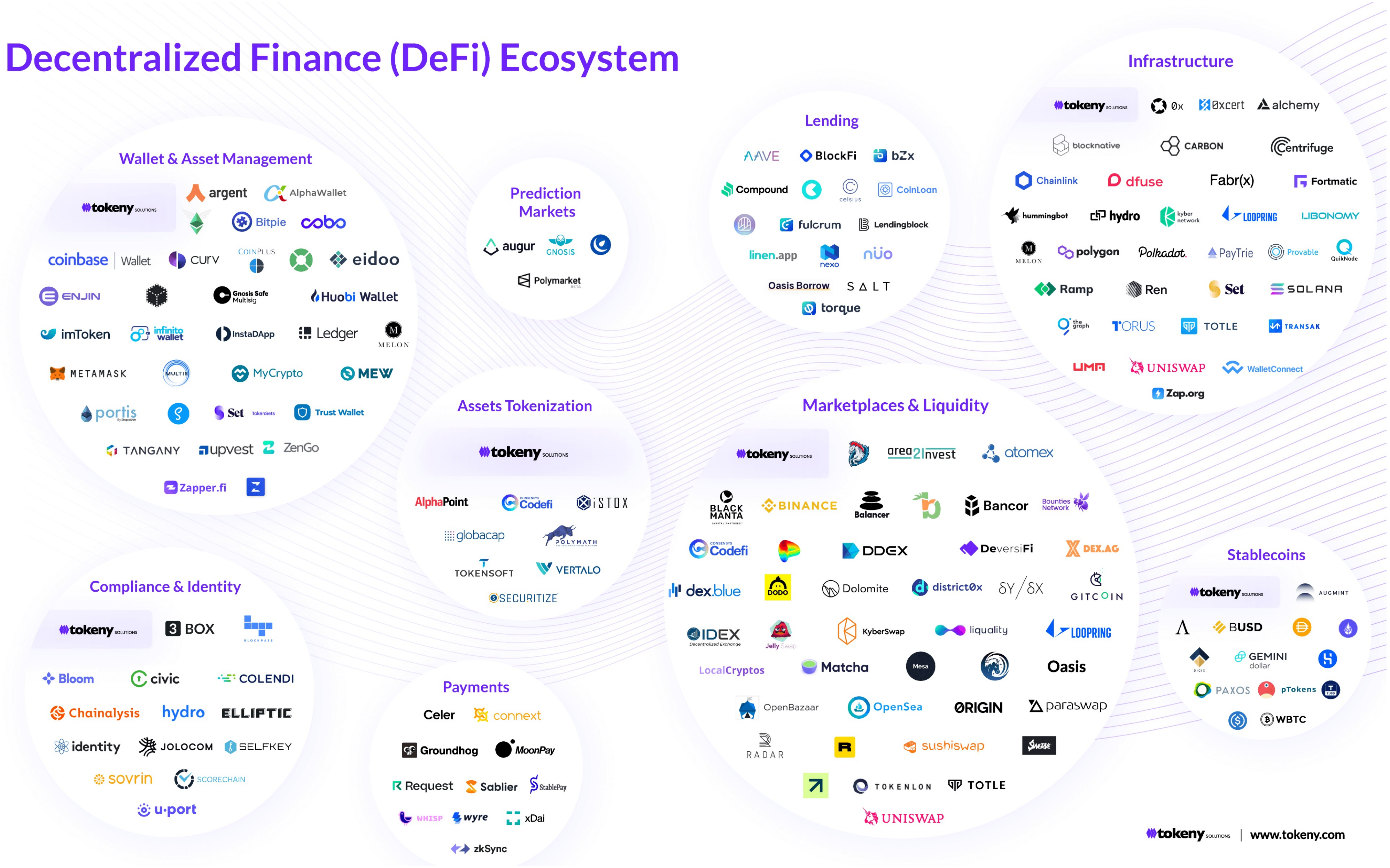
Source: http://www.venturescanner.com/financial-technology

Ethereum DeFi Ecosystem



Source: https://cryptodiffer.com/news/ethereum-defi-ecosystem/

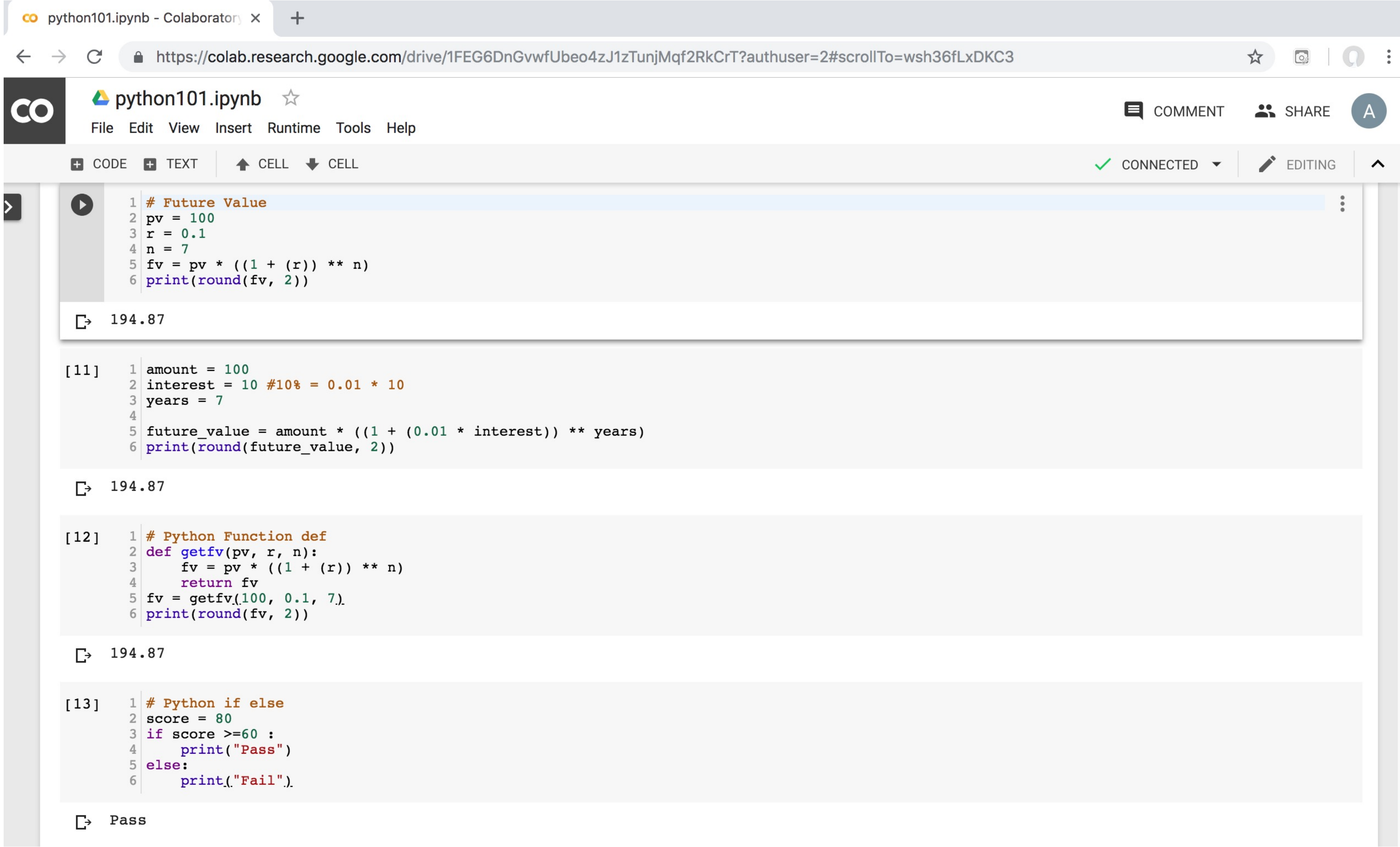
Decentralized Finance (DeFi) Ecosystem



Source: https://tokeny.com/defi-ecosystem/

Python in Google Colab (Python101)

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT



```
# Future Value
pv = 100
r = 0.1
n = 7
fv = pv * ((1 + (r)) ** n)
print(round(fv, 2))
```

```
194.87
```

[11]

```
amount = 100
interest = 10 #10% = 0.01 * 10
years = 7

future_value = amount * ((1 + (0.01 * interest)) ** years)
print(round(future_value, 2))
```

```
194.87
```

[12]

```
# Python Function def
def getfv(pv, r, n):
    fv = pv * ((1 + (r)) ** n)
    return fv
fv = getfv(100, 0.1, 7)
print(round(fv, 2))
```

```
194.87
```

[13]

```
# Python if else
score = 80
if score >=60 :
    print("Pass")
else:
    print("Fail")
```

```
Pass
```

https://tinyurl.com/aintpupython101

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