AI in FinTech: Metaverse, Web3, DeFi, NFT, Financial Services Innovation and Applications

1121AIFQA02
MBA, IM, NTPU (M5276) (Fall 2023)
Tue 2, 3, 4 (9:10-12:00) (B3F17)

https://meet.google.com/paj-zhhj-mya

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2023-09-19

Syllabus

Week	Date	Subject/Topics
1	2023/09/12	Introduction to Artificial Intelligence in Finance and Quantitative Analysis
2	2023/09/19	AI in FinTech: Metaverse, Web3, DeFi, NFT, Financial Services Innovation and Applications
3	2023/09/26	Investing Psychology and Behavioral Finance
4	2023/10/03	Event Studies in Finance
5	2023/10/10	National Day (Day off)
6	2023/10/17	Case Study on AI in Finance and Quantitative Analysis I

Syllabus

Week	Date	Subject/Topics
7	2023/10/24	Finance Theory and Data-Driven Finance
8	2023/10/31	Midterm Project Report
9	2023/11/07	Financial Econometrics
10	2023/11/14	AI-First Finance
11	2023/11/21	Industry Practices of AI in Finance and Quantitative Analysis
12	2023/11/28	Case Study on AI in Finance and Quantitative Analysis II

Syllabus

Week	Date	Subject/Topics
13	2023/12/05	Deep Learning in Finance; Reinforcement Learning in Finance
14	2023/12/12	Algorithmic Trading; Risk Management; Trading Bot and Event-Based Backtesting
15	2023/12/19	Final Project Report I
16	2023/12/26	Final Project Report II

AI in FinTech: Metaverse, Web3, DeFi, NFT, Financial Services Innovation and Applications

AI

in

FinTech

FinTech ABCD

AI

Block Chain

Cloud Computing

Big Data

Decentralized Finance (DeFi)

Block Chain Financial Technology

Block Chain & Bitcoin
(BTC)

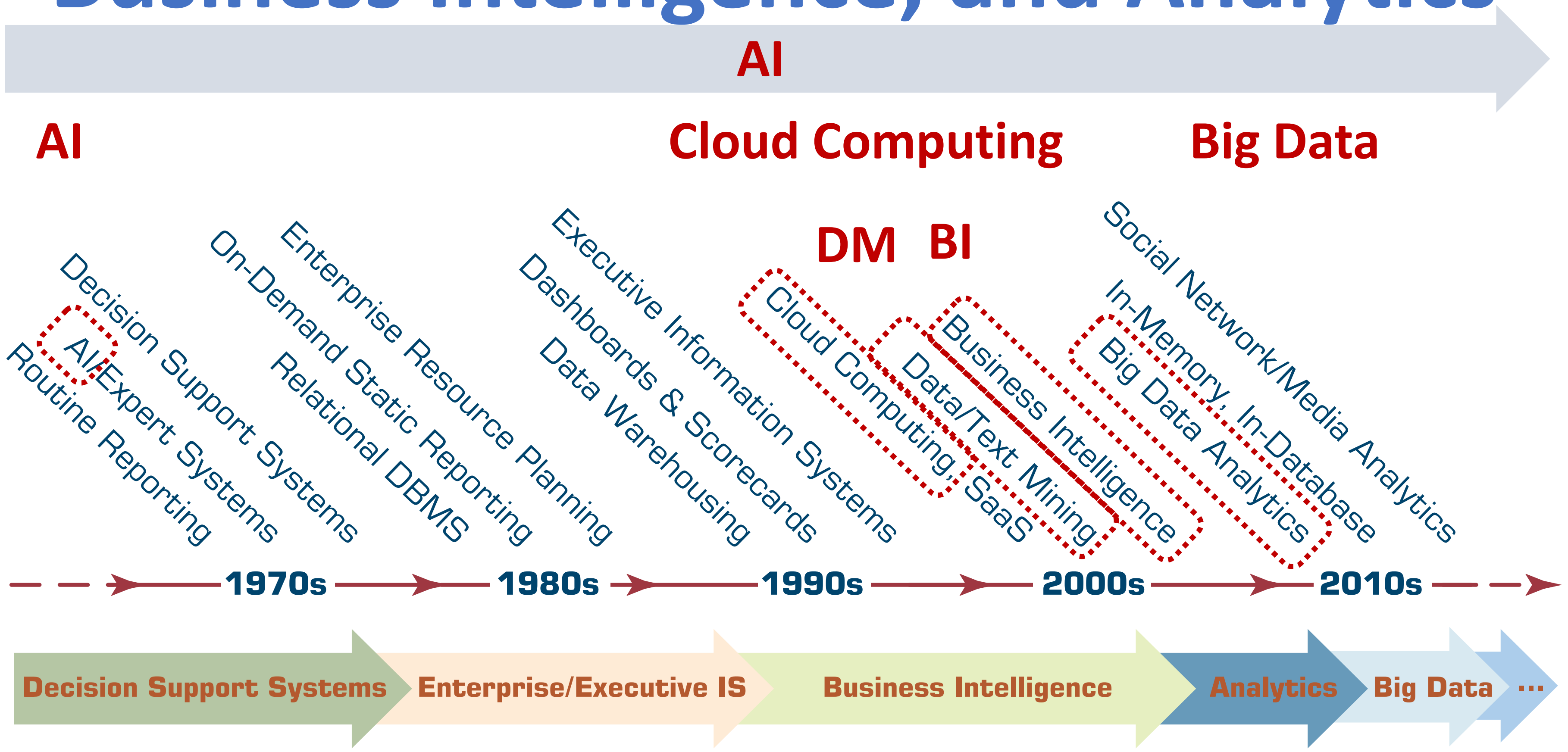
Smart Contract & Ethereum
(ETH)

Decentralized Application
(DApp)

Artificial Intelligence (AI)

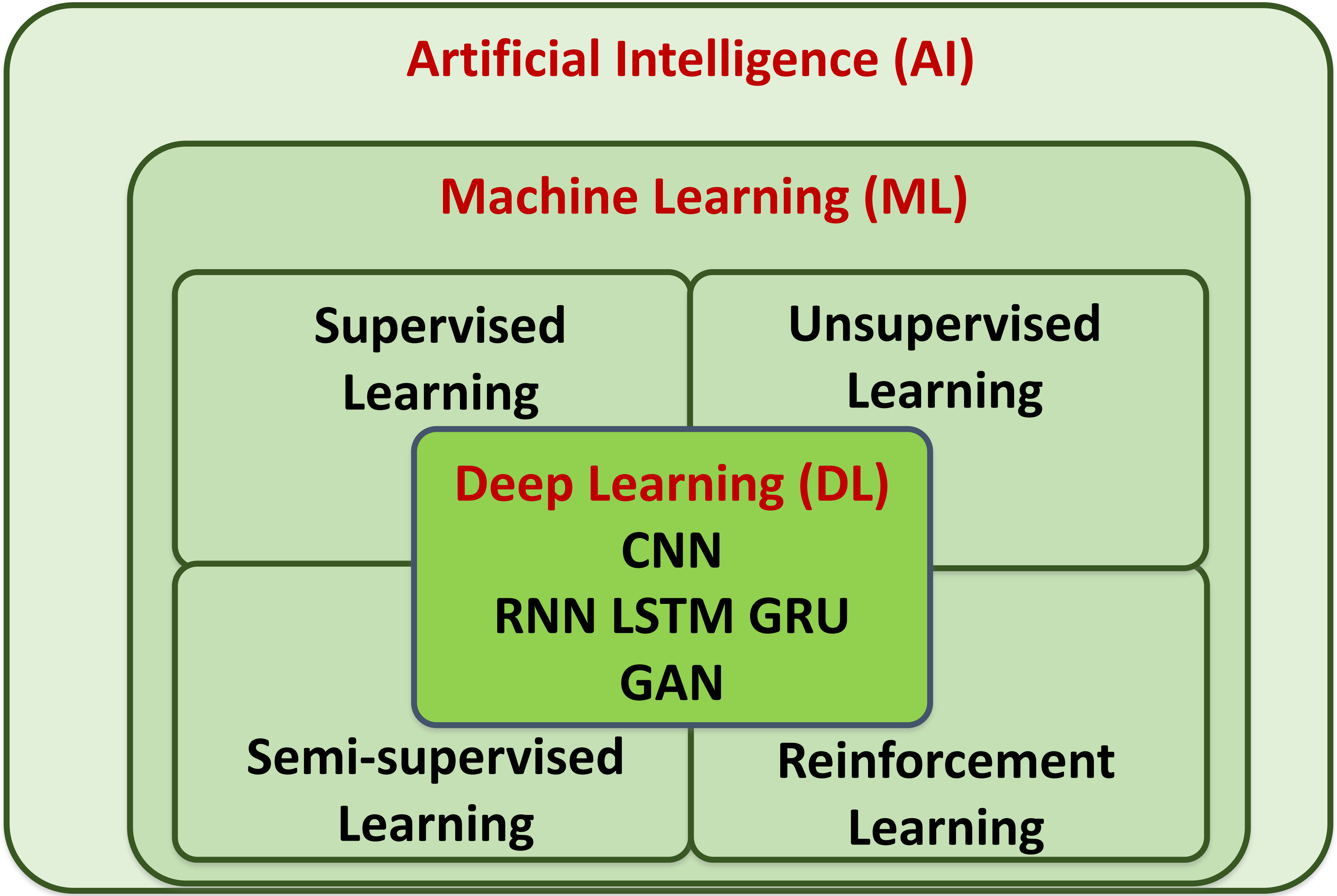
AI, Big Data, Cloud Computing

Evolution of Decision Support, Business Intelligence, and Analytics



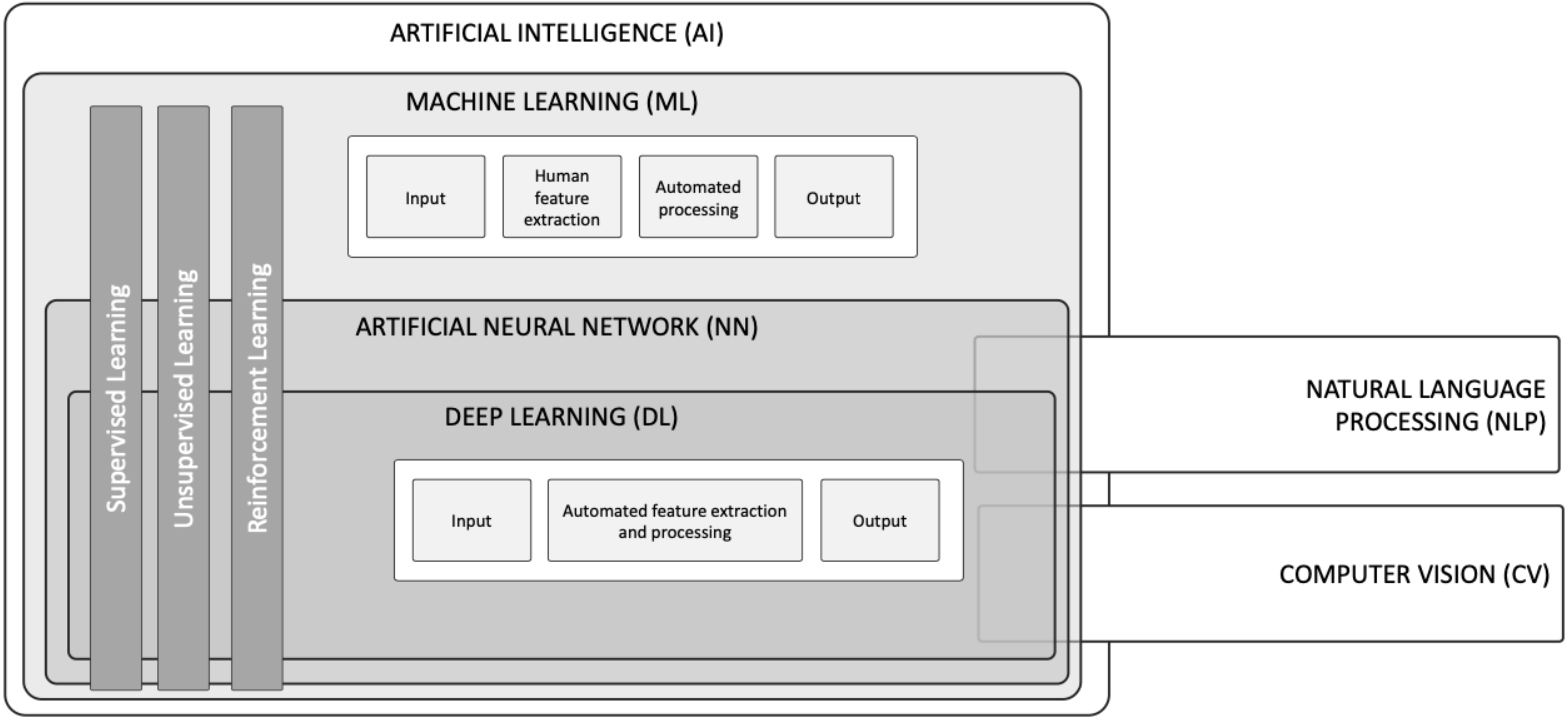
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017),
Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

AI, ML, DL



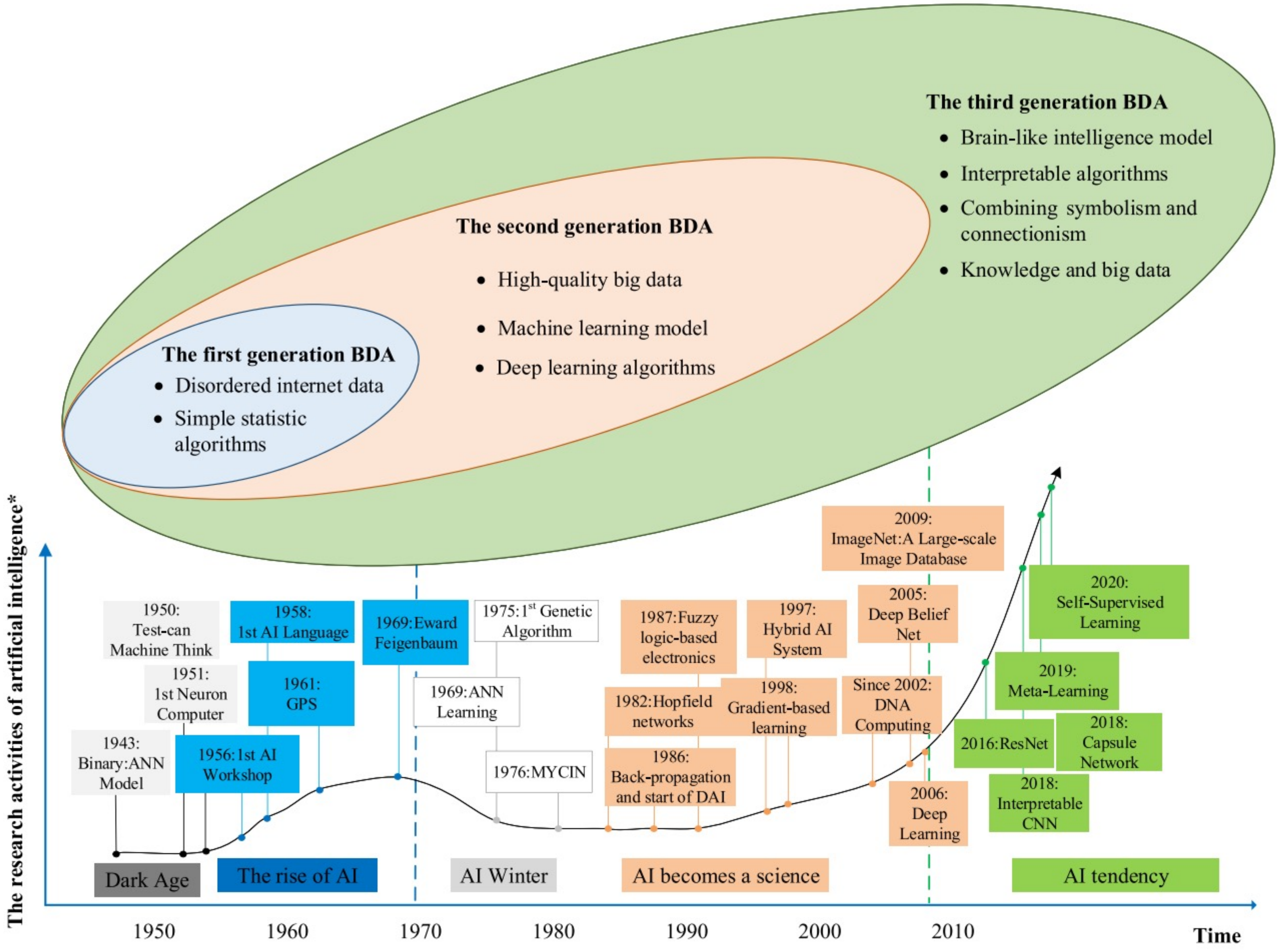
Source: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/deep_learning.html

AI, ML, NN, DL



Source: Schoormann, T., Strobel, G., Möller, F., Petrik, D., & Zschech, P. (2023).
Artificial Intelligence for Sustainability—A Systematic Review of Information Systems Literature. Communications of the Association for Information Systems, 52(1), 8.

AI and Big Data Analytics (BDA)



Source: Wang, Junliang, Chuqiao Xu, Jie Zhang, and Ray Zhong (2022). "Big data analytics for intelligent manufacturing systems: A review." Journal of Manufacturing Systems 62 (2022): 738-752.

Definition
of
Artificial Intelligence
(A.I.)

Artificial Intelligence

"… the science and

engineering

of

making

intelligent machines"

(John McCarthy, 1955)

Source: https://digitalintelligencetoday.com/artificial-intelligence-defined-useful-list-of-popular-definitions-from-business-and-science/

Artificial Intelligence

"… technology that thinks and acts like humans"

Source: https://digitalintelligencetoday.com/artificial-intelligence-defined-useful-list-of-popular-definitions-from-business-and-science/

Artificial Intelligence

"… intelligence exhibited by machines or software"

Source: https://digitalintelligencetoday.com/artificial-intelligence-defined-useful-list-of-popular-definitions-from-business-and-science/

4 Approaches of AI

Thinking Humanly	Thinking Rationally
Acting Humanly	Acting Rationally

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

4 Approaches of AI

2. Thinking Humanly: The Cognitive Modeling Approach	3. Thinking Rationally: The “Laws of Thought” Approach
1. Acting Humanly: The Turing Test Approach (1950)	4. Acting Rationally: The Rational Agent Approach

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

AI Acting Humanly:
The Turing Test Approach
(Alan Turing, 1950)

- Knowledge Representation
- Automated Reasoning
- Machine Learning (ML)
  - Deep Learning (DL)
- Computer Vision (Image, Video)
- Natural Language Processing (NLP)
- Robotics

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

FinTech

Financial Technology
FinTech

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

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

Financial Technology

Financial Services

FinTech: Financial Services Innovation

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

FinTech:

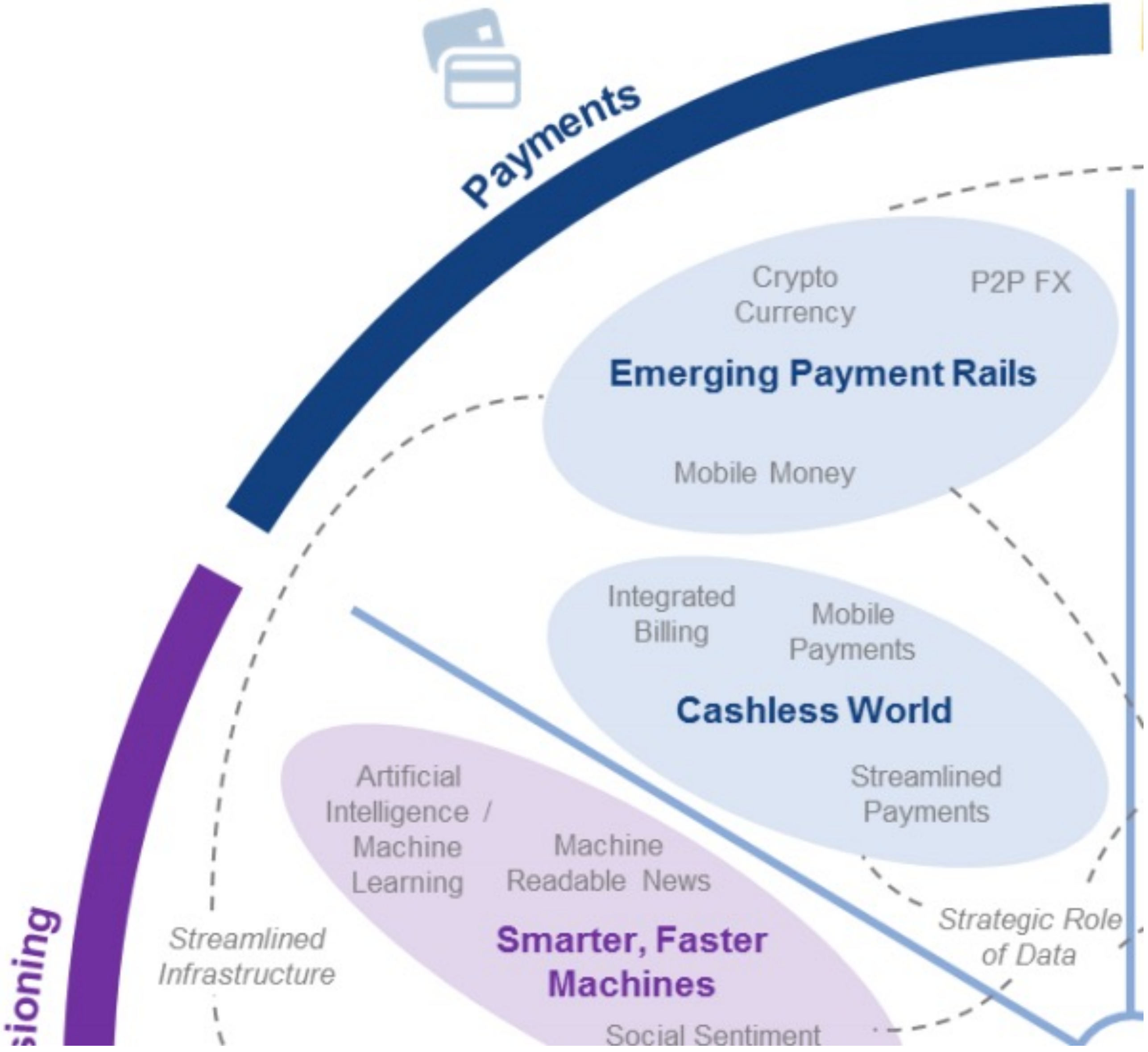
Financial Services Innovation

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

1

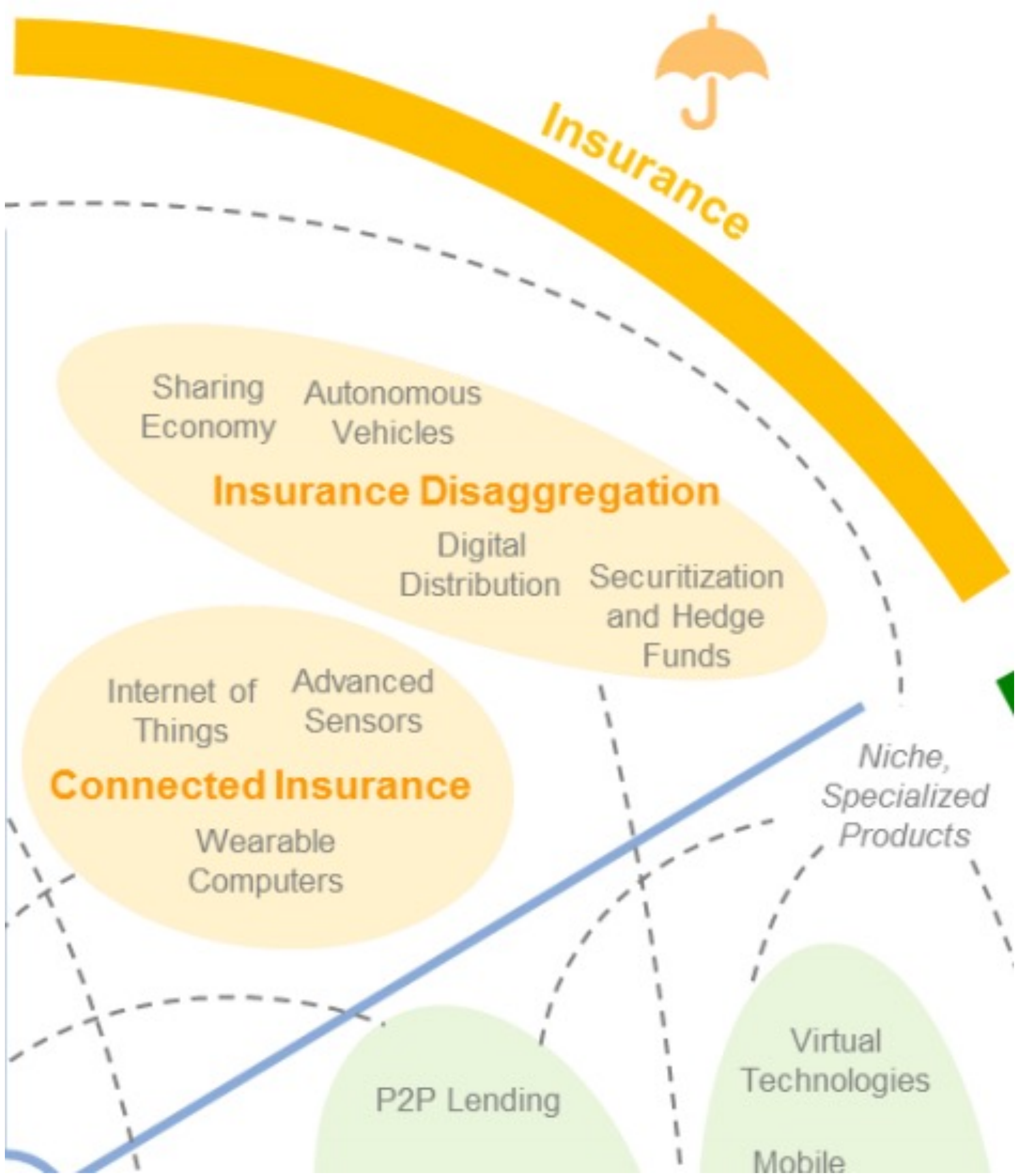
FinTech: Payment



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

2

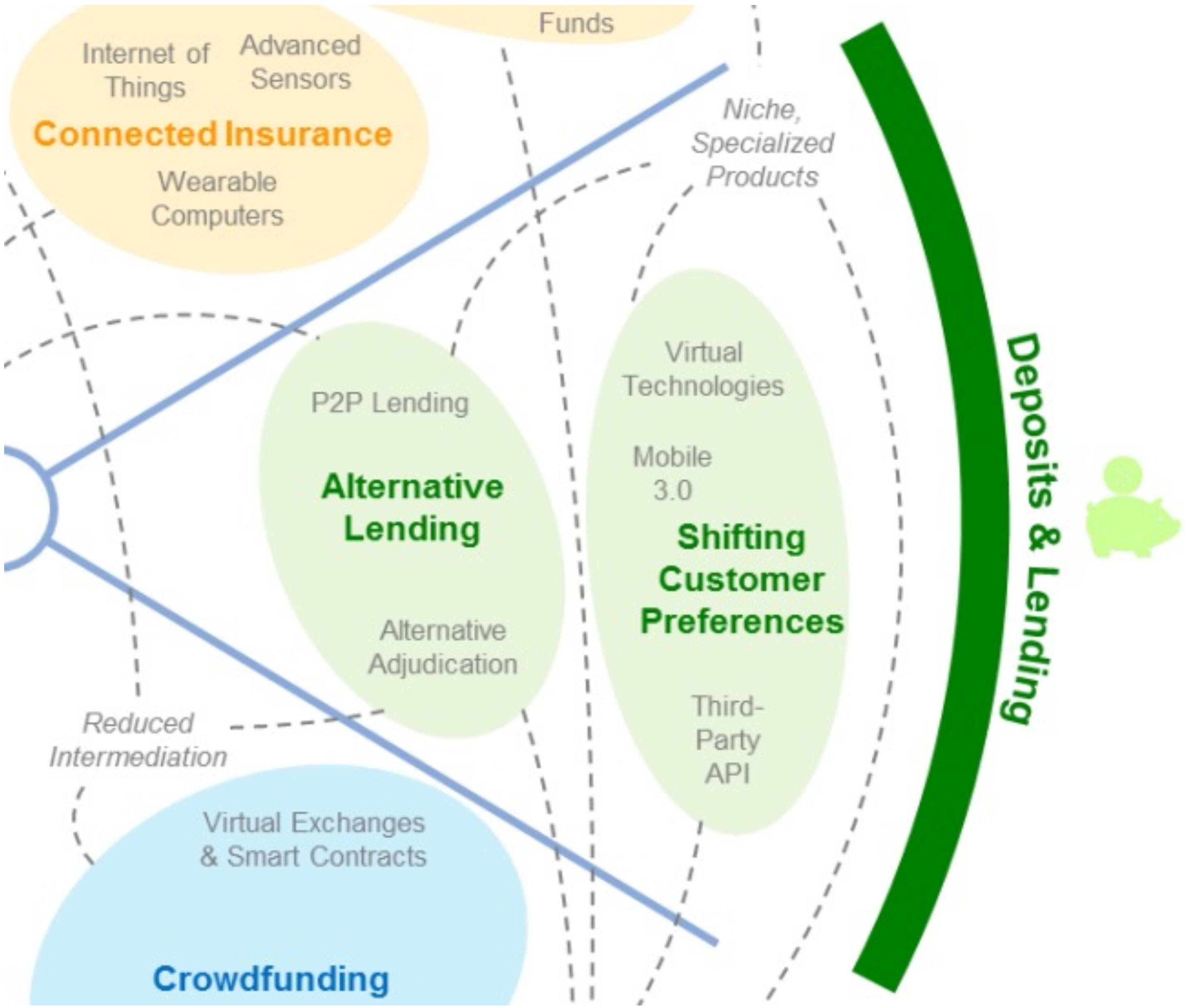
FinTech: Insurance



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

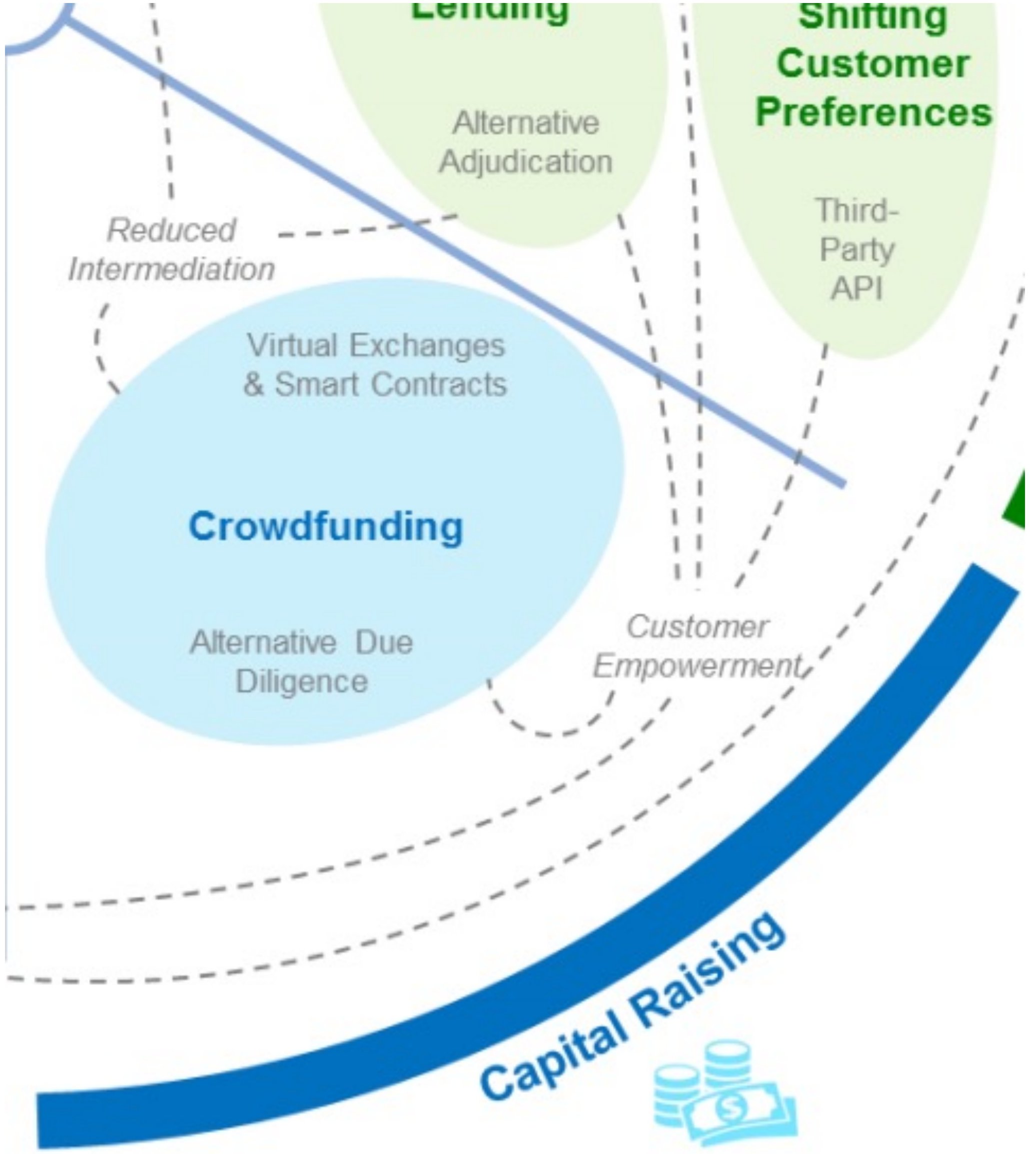
3

FinTech: Deposits & Lending



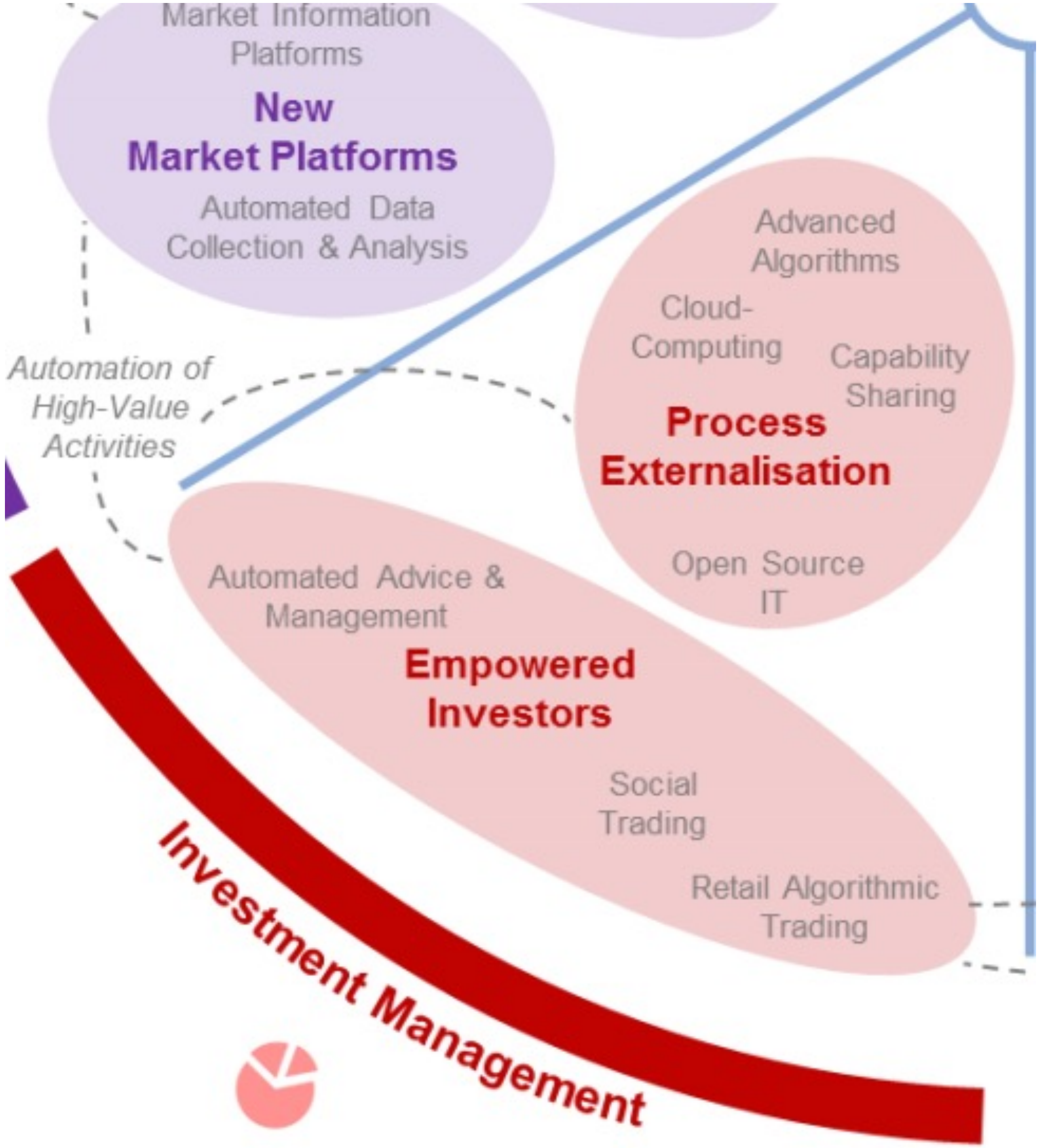
Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

4 FinTech: Capital Raising



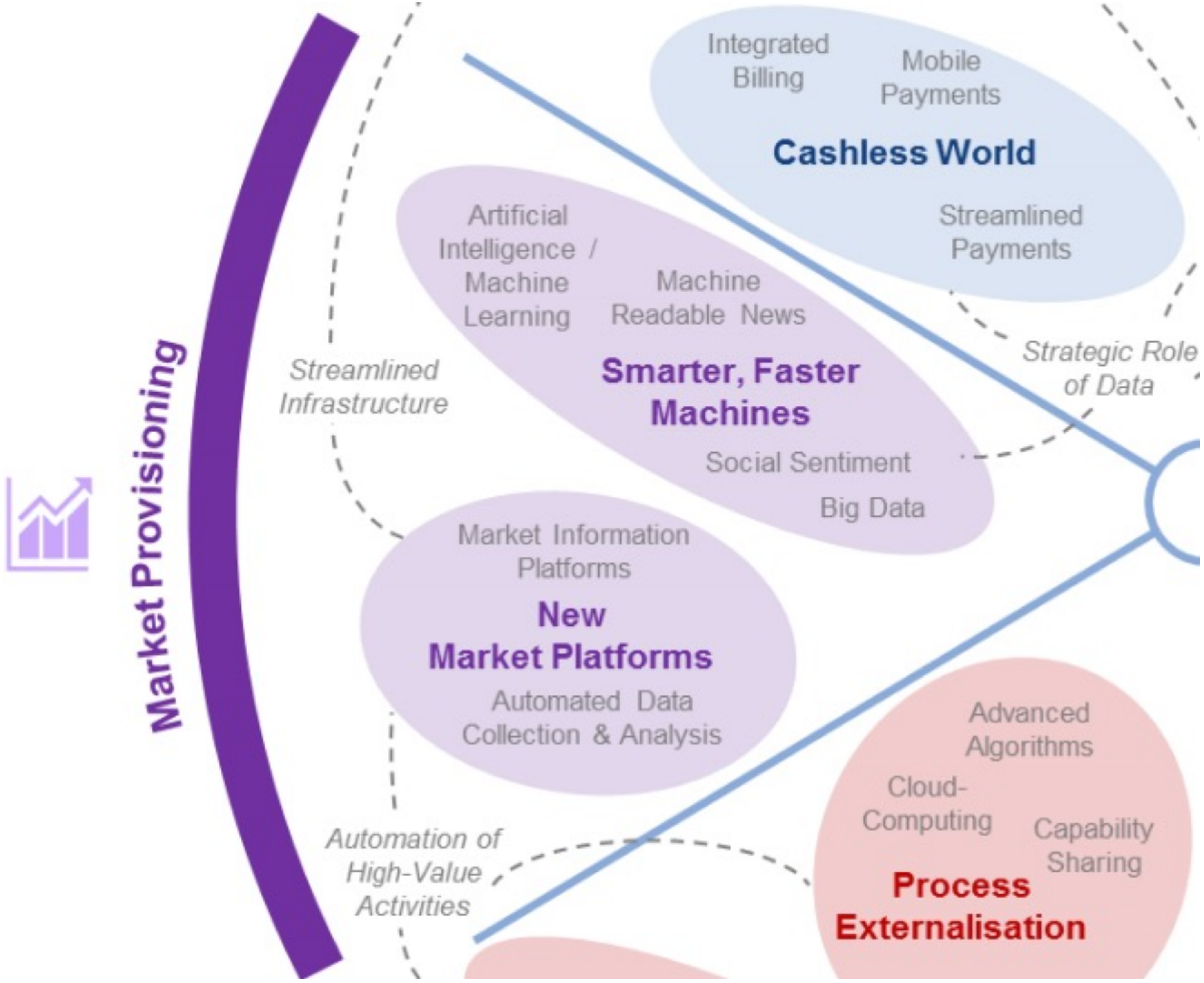
Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

5 FinTech: Investment Management



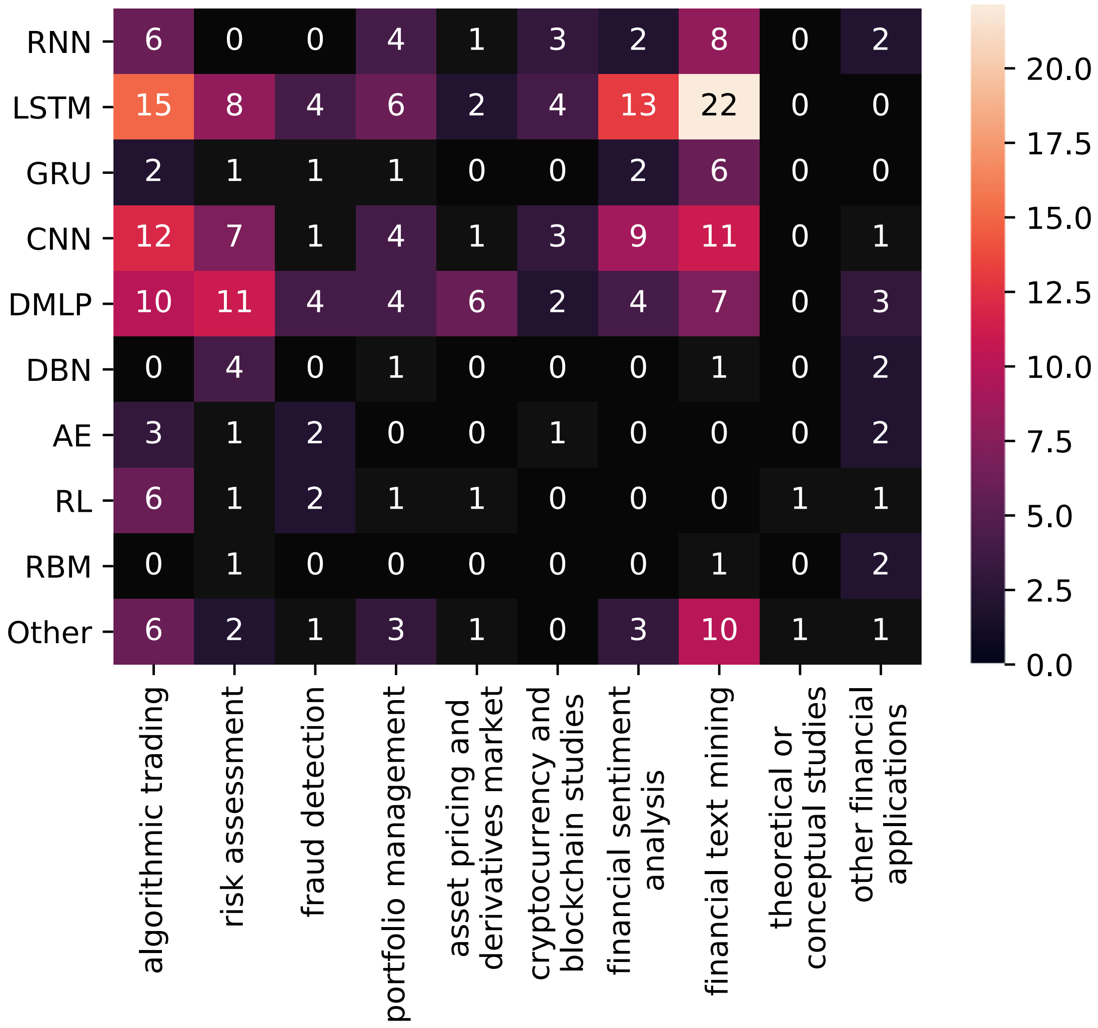
Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

6 FinTech: Market Provisioning



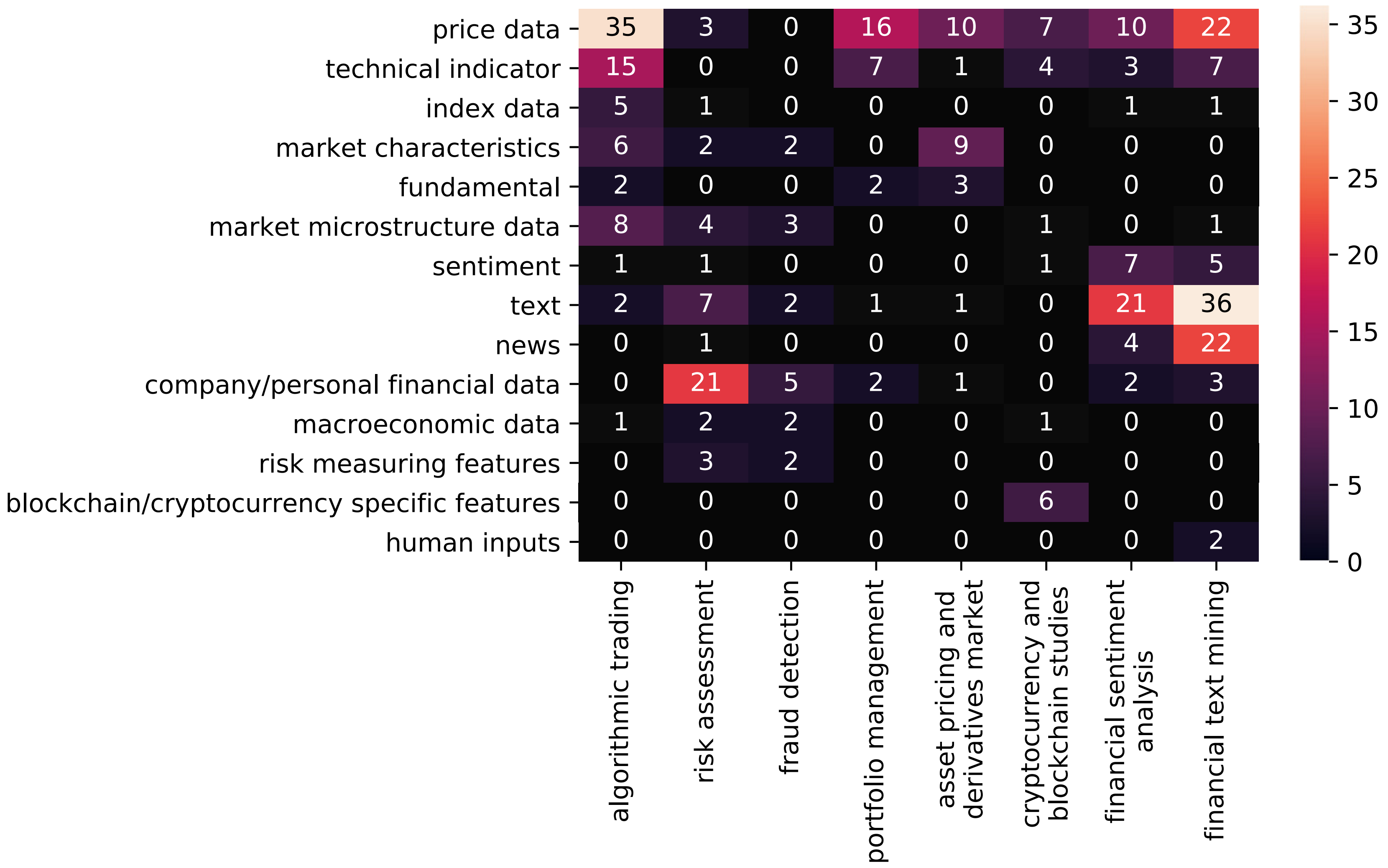
Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

Deep learning for financial applications: Topic-Model Heatmap



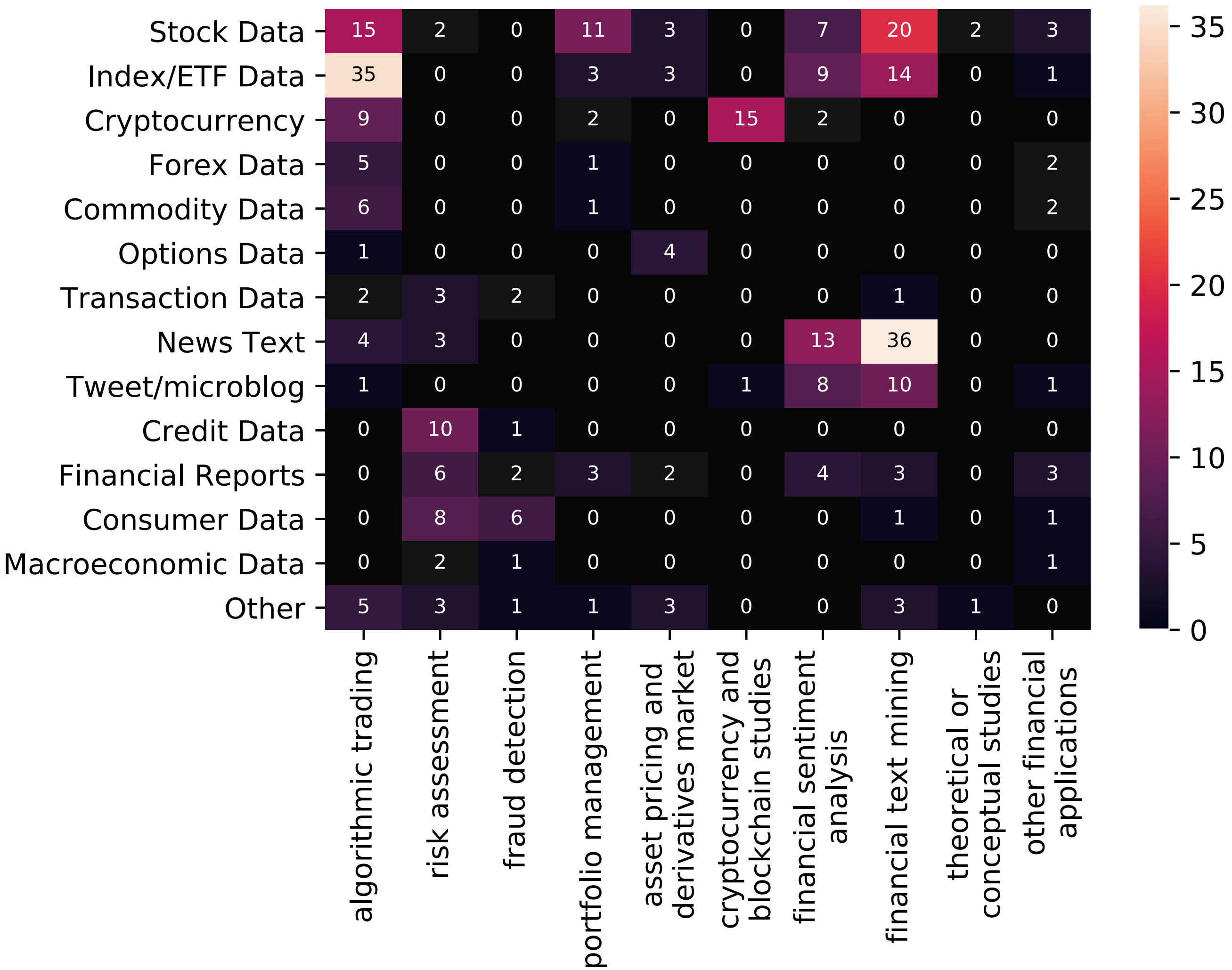
Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications: Topic-Feature Heatmap



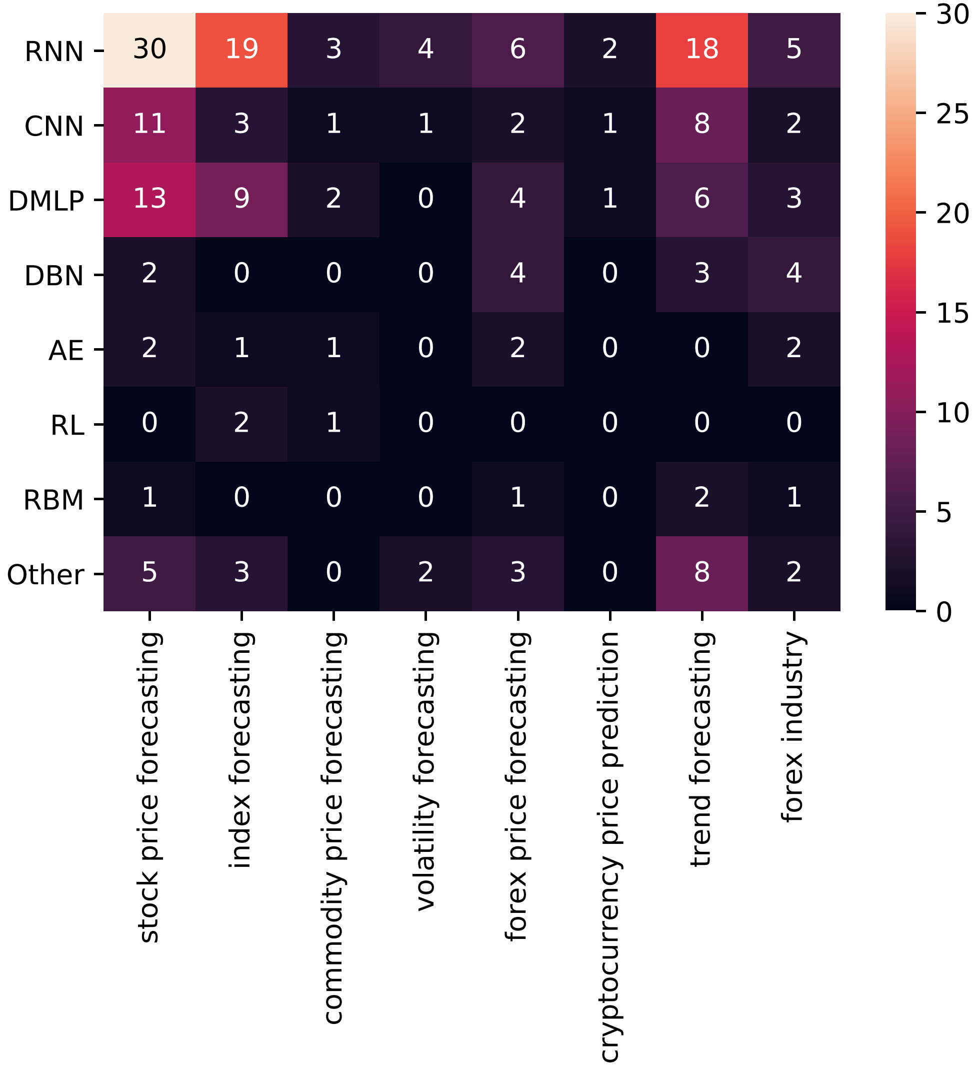
Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications: Topic-Dataset Heatmap



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



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:

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

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
[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	–	–

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:

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	–

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:

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

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:
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

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 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

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: 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

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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

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:

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

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 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.

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	–

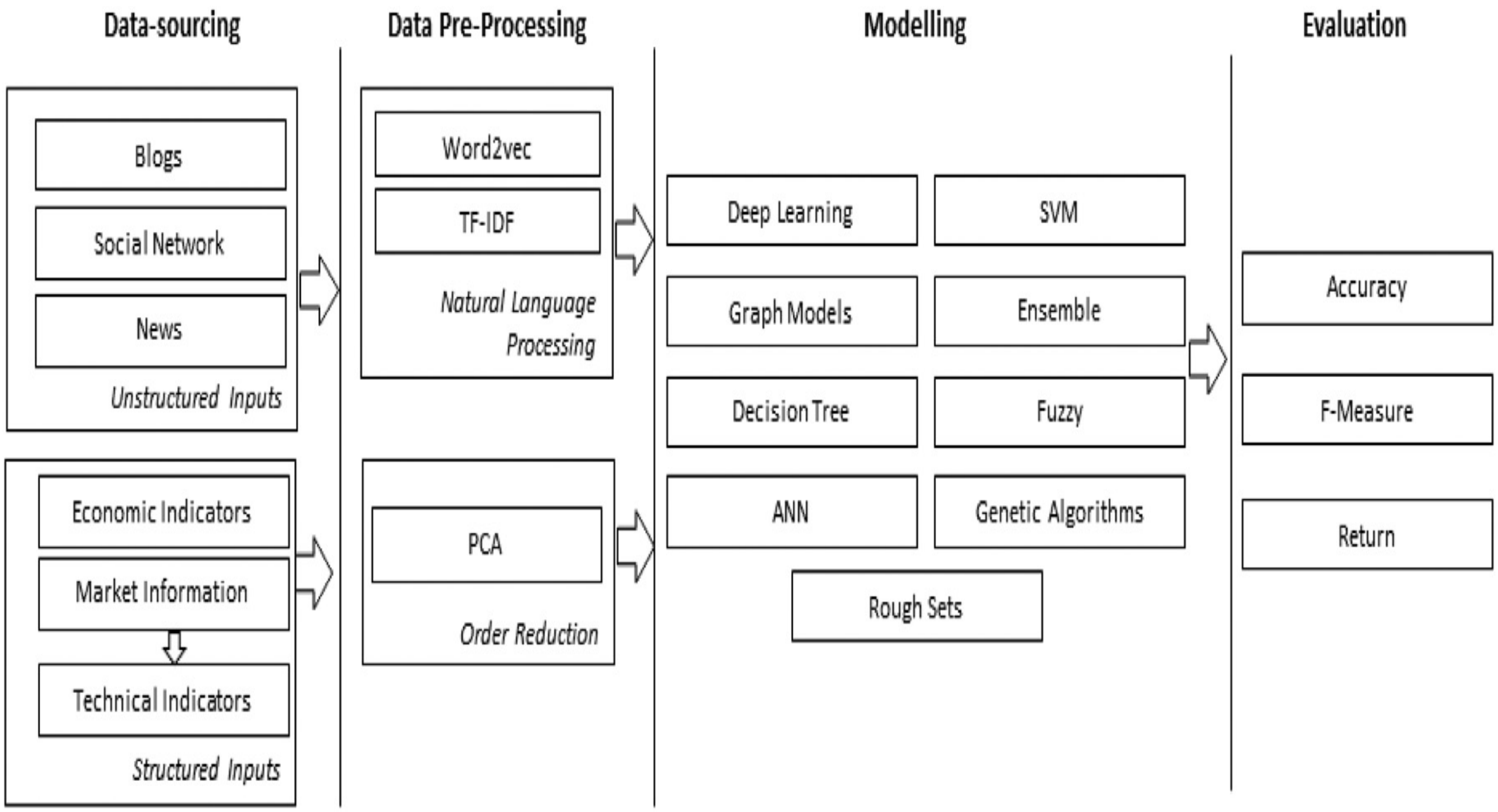
Source: Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020), "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019." Applied Soft Computing 90 (2020): 106181.

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.

Modelling Strategy to Forecast Carbon Emissions with AI

DATA

COLLECTING DATA

Target Variables
- Total emissions
- Scope 1, Scope 2 and Scope 3 emissions

Predictors
- Scale of operations
- Business model
- Technology advancement
- Energy factors
- Environmental factors

Data source
- Thomson Reuters Eikon
- World Bank
- IEA

PRE- PROCESSING DATA

Prefilter low quality data
- Insufficient predictors
- Abnormal trends

Data-transformation
- Log transformation

Outliers
- Remove outliers
- Winsorise outliers

Missing values
- List-wide deletion
- Imputation with historical data and peer groups

PREDICTION MODEL

PREDICTOR SELECTION

Classification
- GICS Sector
- GICS Group
- NAICS Sector
- Reclassified NAICS Sector
- Reclassified GICS Group

Firm characteristics
- GBB model
- GLS model
- Combined model
- Extended model
- Step-wise model

Environmental factors
- Carbon law
- Country income group

Energy

Fiscal Years

BUILDING BASE-LEANERS

Linear models
- OLS
- Elastic Net

Non linear models
- Neural Network
- K Nearest Neighbours

Decision tree ensembles
- Random Forests
- Extreme Gradient Boosting

BUILDING META-LEARNERS

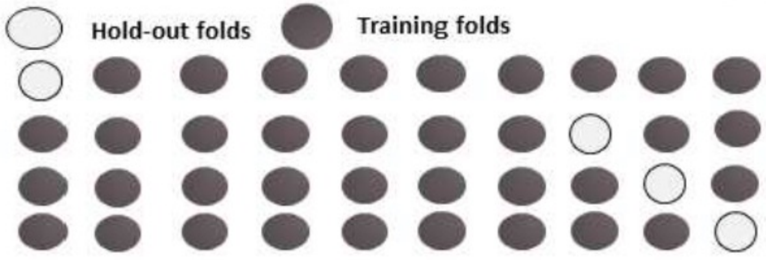
Simple combination
- Arithmetic mean
- Median

Stacked generalization
- Meta OLS
- Meta Elastic Net
- Meta XGB

Hyper-parameter optimization metrics
- Mean Absolute Error (MAE)

MODEL EVALUATION

Double 10-Fold division for base-learners and meta-learners



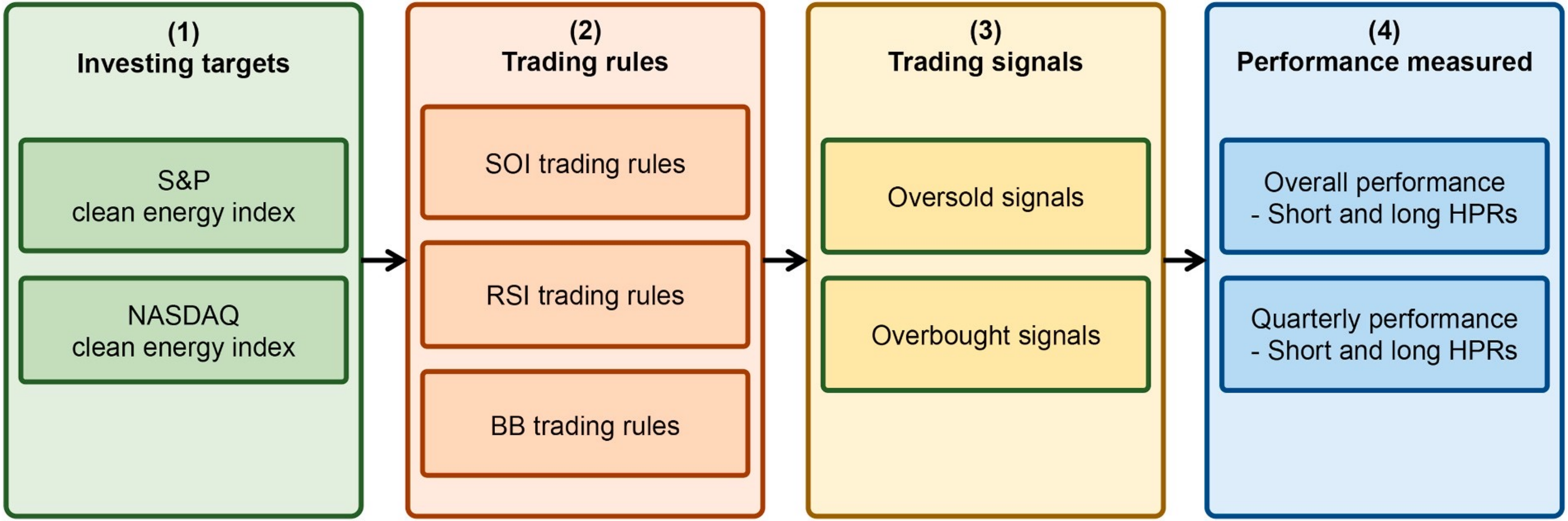
Main Evaluation metrics:
- Mean Absolute Error (MAE)
- Wilcoxon Signed-Rank test

Robustness Tests
- Alternative measures (MAPE, PPAR)
- Test of percentile ranking, mean difference and SP500 membership subgroup

Source: Brière, M., Keip, M., & Le Berthe, T. (2022). Artificial Intelligence for Sustainable Finance: Why it May Help. Available at SSRN 4252329.

The Research Framework

Do clean energy indices outperform using contrarian strategies



Source, Min-Yuh Day and Yensen Ni (2023), "Do clean energy indices outperform using contrarian strategies based on contrarian trading rules?", Energy, Volume 272, 1 June 2023, 127113.

Artificial Intelligence for Sustainable Finance

- **Why AI may help sustainable finance?**
  - Brière, M., Keip, M., & Le Berthe, T. (2022). Artificial Intelligence for Sustainable Finance: Why it May Help. Available at SSRN 4252329.
- **How does artificial intelligence boost sustainable development?**
  - Schoormann, T., Strobel, G., Möller, F., Petrik, D., & Zschech, P. (2023). Artificial Intelligence for Sustainability—A Systematic Review of Information Systems Literature. Communications of the Association for Information Systems, 52(1), 8.
- **Does sustainability generate better financial performance?**
  - Atz, U., Van Holt, T., Liu, Z. Z., & Bruno, C. C. (2023). Does sustainability generate better financial performance? review, meta-analysis, and propositions. Journal of Sustainable Finance & Investment, 13(1), 802-825.
- **What are the major research topics in AI for Sustainable finance?**
  - Kumar, S., Sharma, D., Rao, S., Lim, W. M., & Mangla, S. K. (2022). Past, present, and future of sustainable finance: Insights from big data analytics through machine learning of scholarly research. Annals of Operations Research, 1-44.

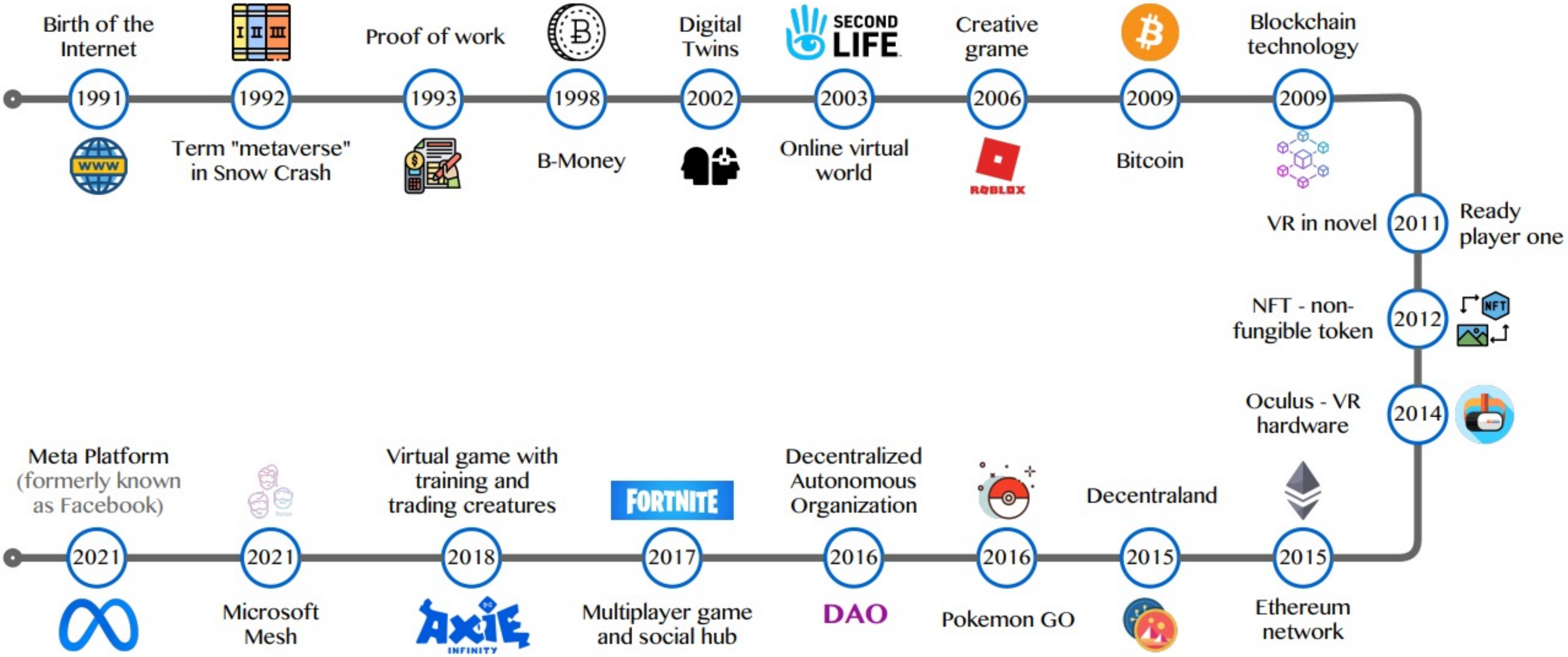
Metaverse

Web3

DeFi

NFT

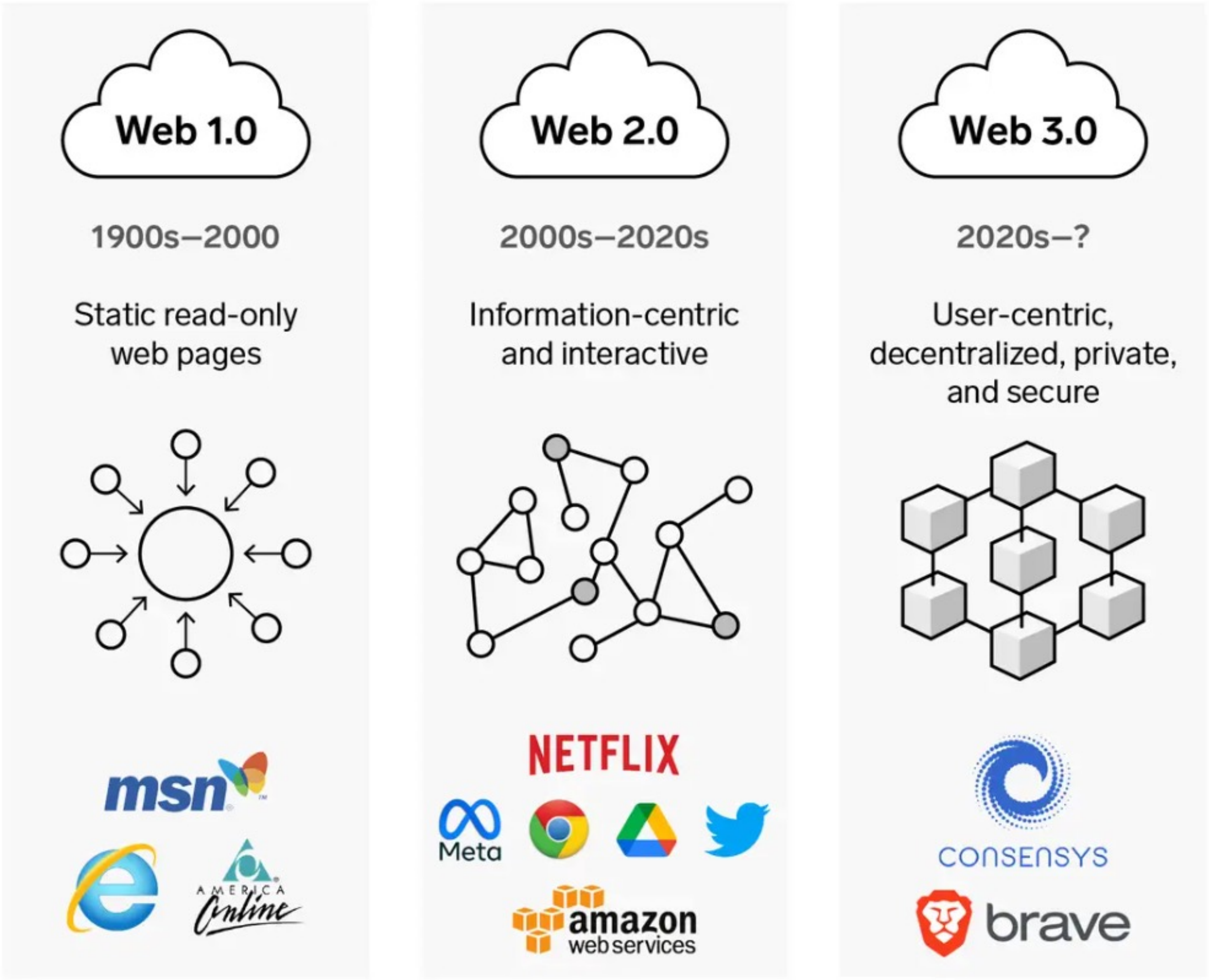
Metaverse Development from 1991 to 2021



Source: Huynh-The, Thien, Quoc-Viet Pham, Xuan-Qui Pham, Thanh Thi Nguyen, Zhu Han, and Dong-Seong Kim (2022). "Artificial Intelligence for the Metaverse: A Survey." arXiv preprint arXiv:2202.10336.

Web3: Decentralized Web

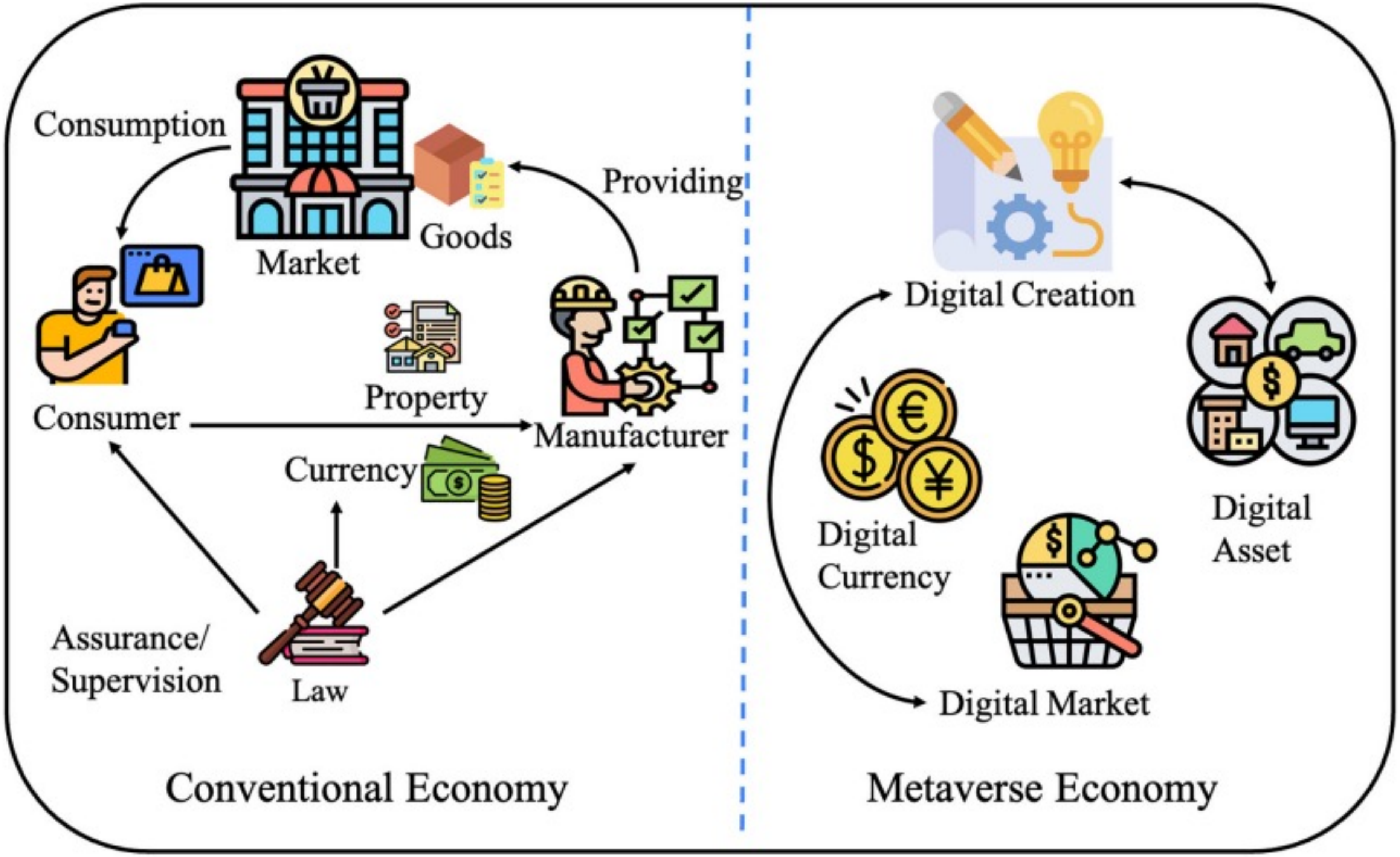
Internet Evolution



1990 2000 2020

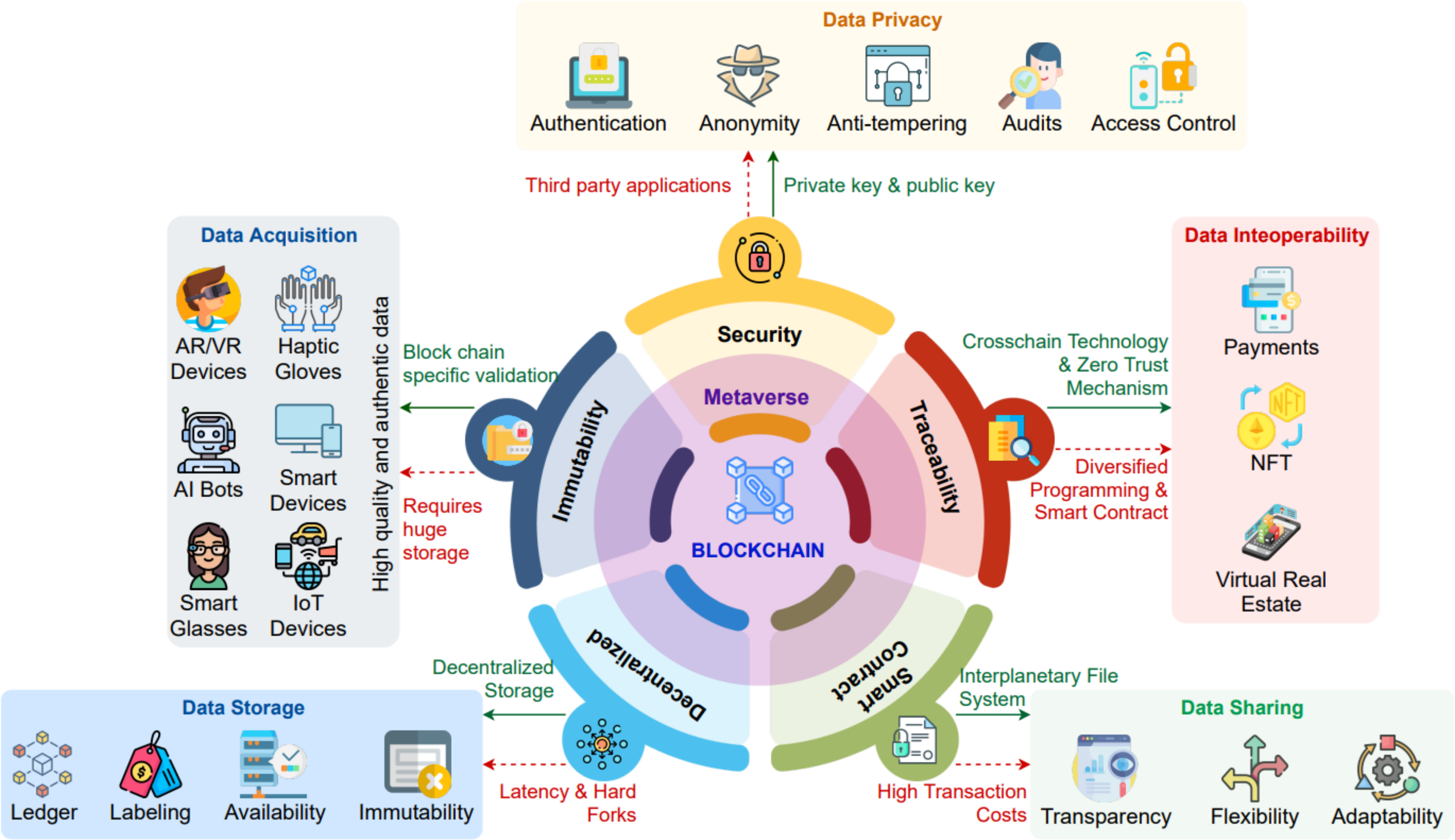
Source: https://www.businessinsider.com/personal-finance/what-is-web3

Metaverse Economy



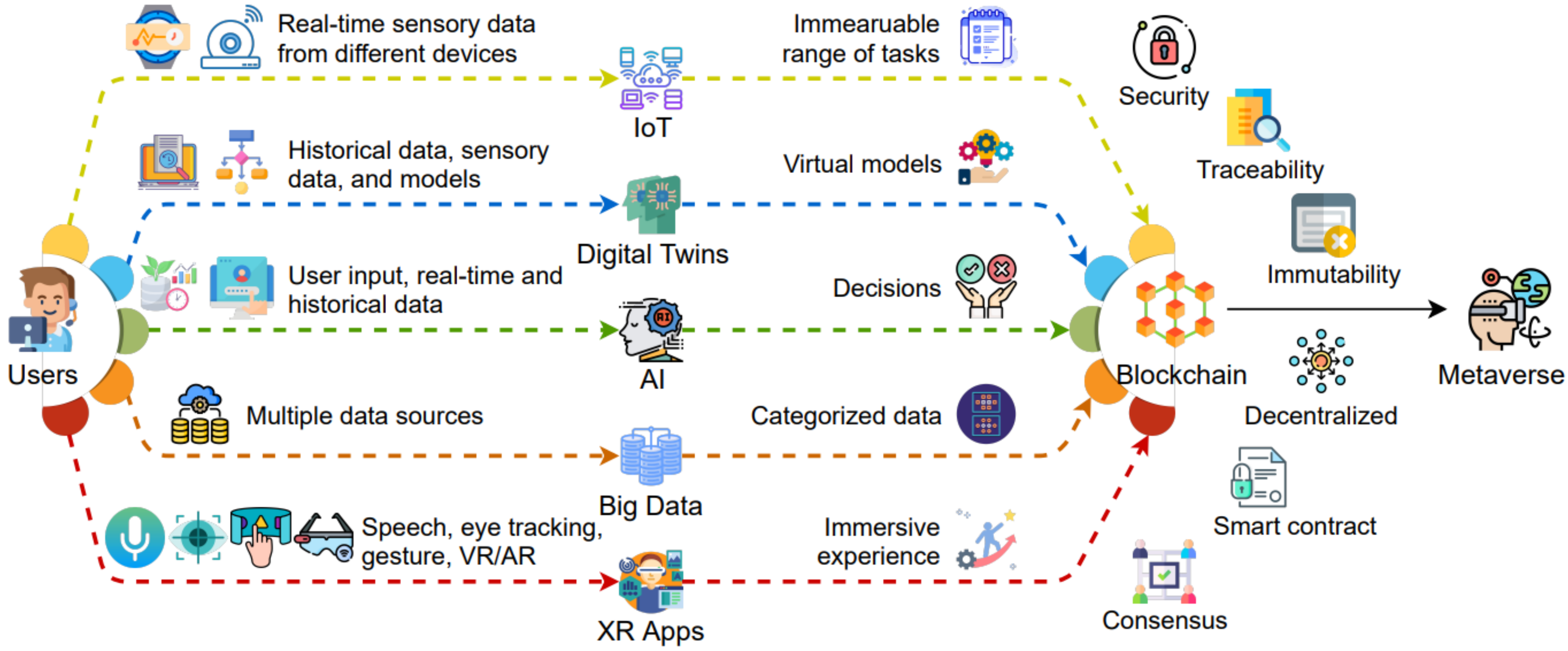
Source: Yang, Qinglin, Yetong Zhao, Huawei Huang, Zehui Xiong, Jiawen Kang, and Zibin Zheng (2022).
"Fusing blockchain and AI with metaverse: A survey." IEEE Open Journal of the Computer Society 3 : 122-136.

Blockchain in the Metaverse



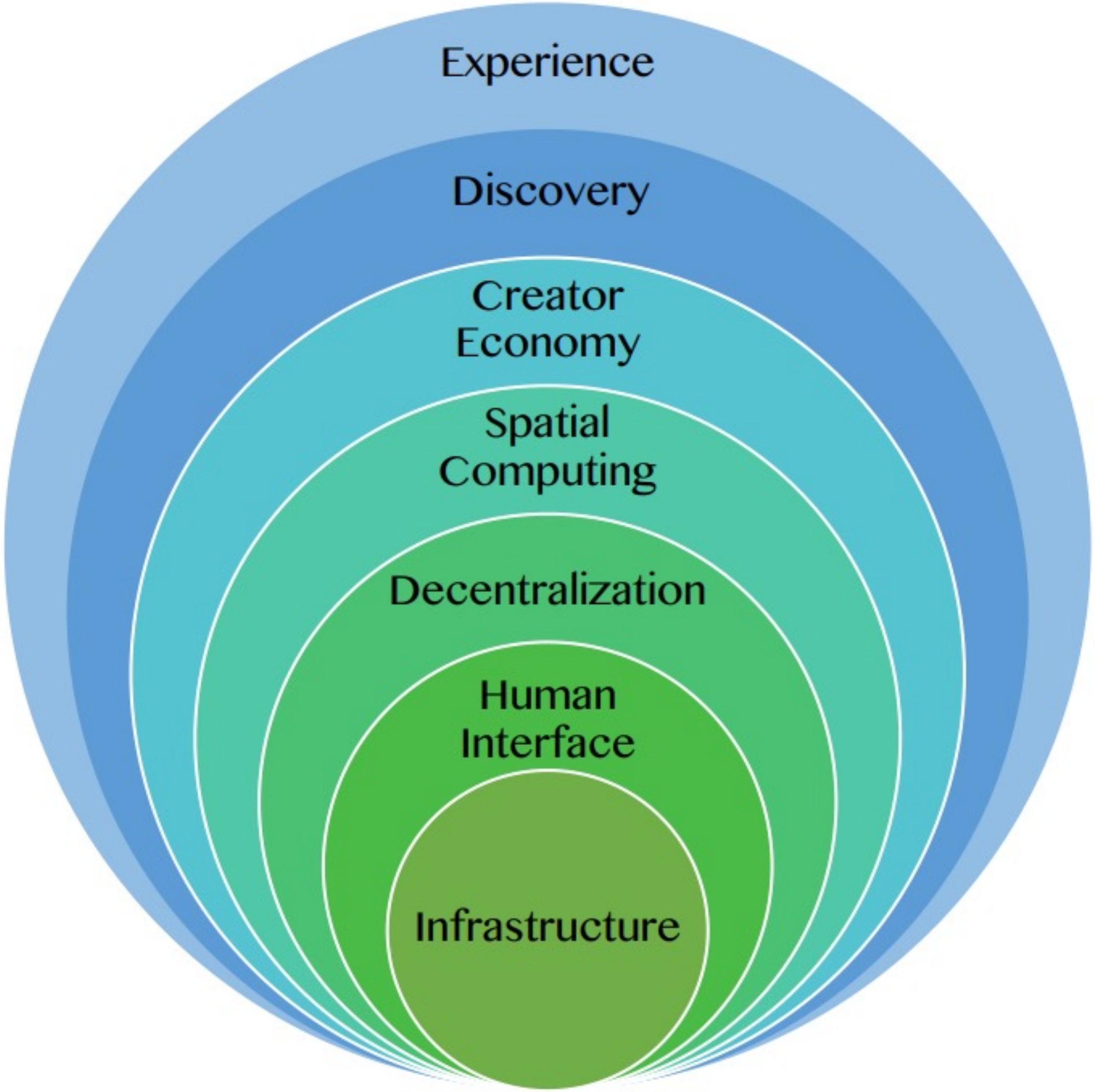
Source: Gadekallu, Thippa Reddy, Thien Huynh-The, Weizheng Wang, Gokul Yenduri, Pasika Ranaweera, Quoc-Viet Pham, Daniel Benevides da Costa, and Madhusanka Liyanage (2022). "Blockchain for the Metaverse: A Review." arXiv preprint arXiv:2203.09738..

Blockchain
for Key Enabling Technologies of the Metaverse



Source: Gadekallu, Thippa Reddy, Thien Huynh-The, Weizheng Wang, Gokul Yenduri, Pasika Ranaweera, Quoc-Viet Pham, Daniel Benevides da Costa, and Madhusanka Liyanage (2022). "Blockchain for the Metaverse: A Review." arXiv preprint arXiv:2203.09738..

Seven Layers of a Metaverse Platform



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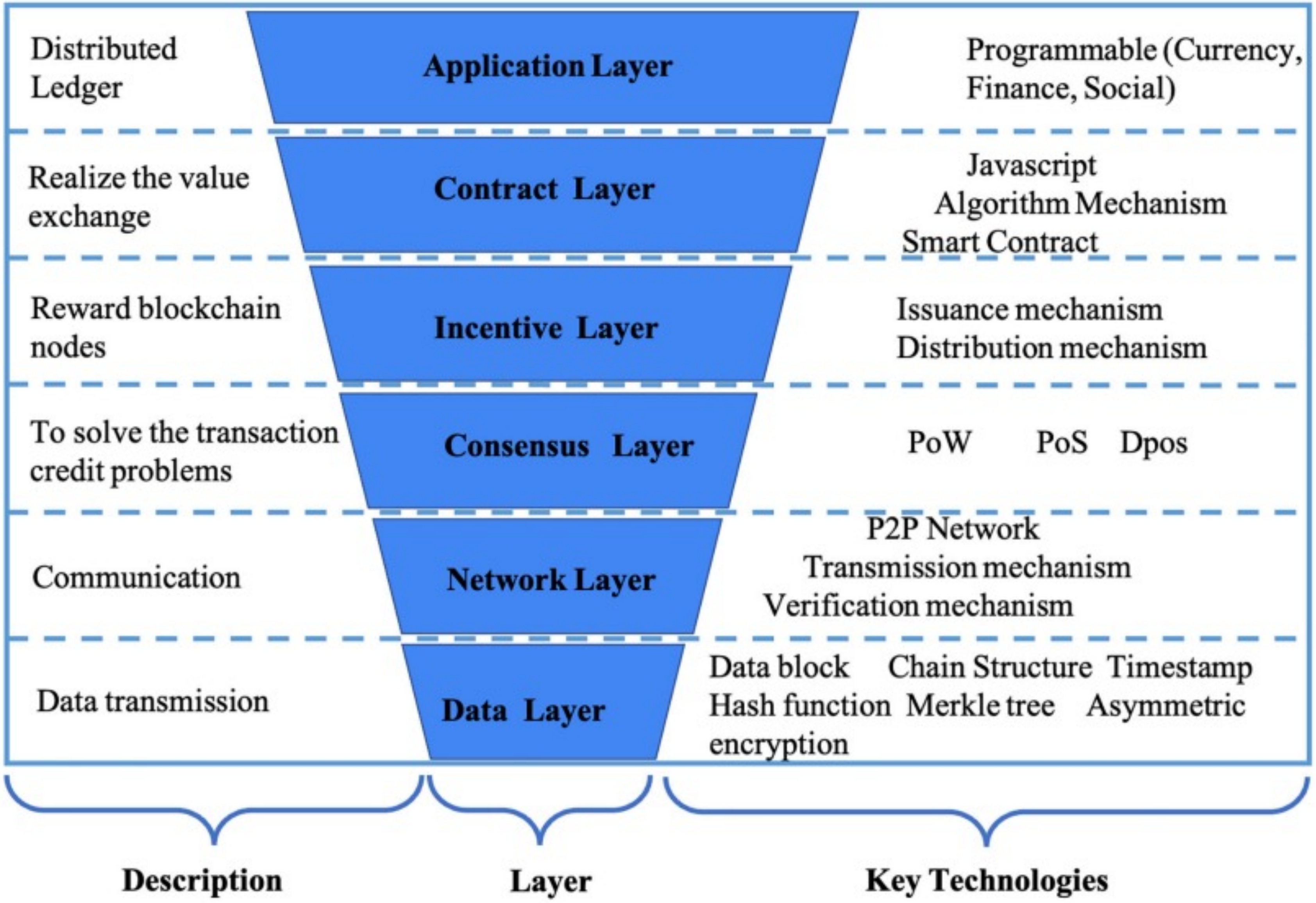
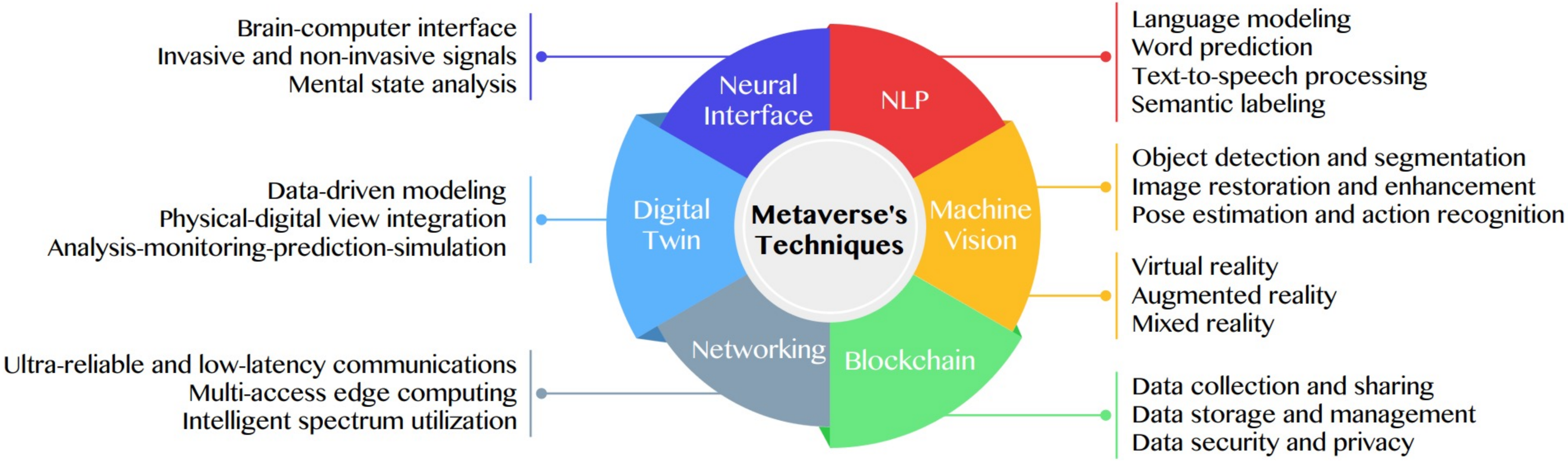
Layered Architecture of Blockchain



Source: Yang, Qinglin, Yetong Zhao, Huawei Huang, Zehui Xiong, Jiawen Kang, and Zibin Zheng (2022). "Fusing blockchain and AI with metaverse: A survey." IEEE Open Journal of the Computer Society 3 : 122-136.

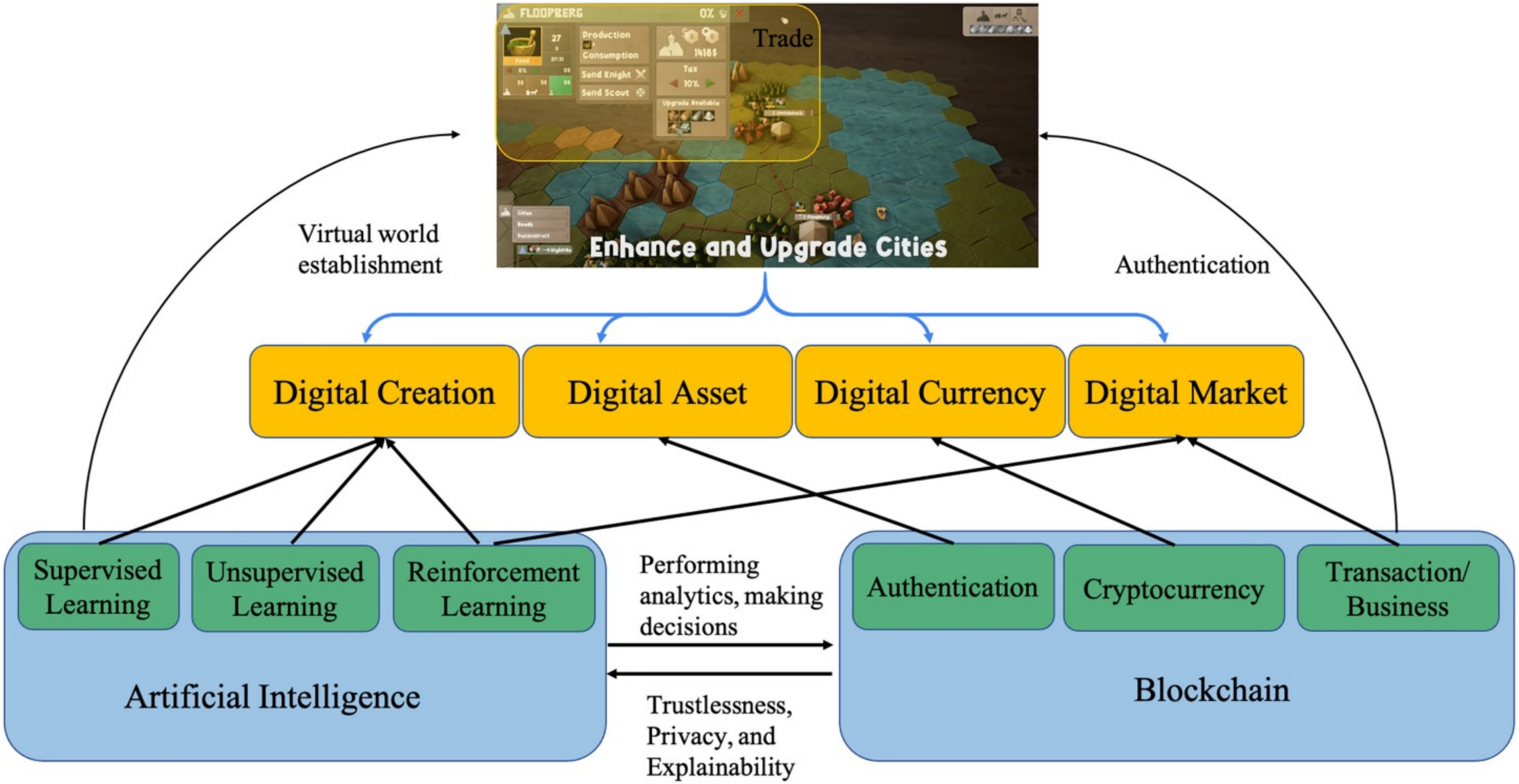
Primary Technical Aspects in the Metaverse

AI with ML algorithms and DL architectures is advancing the user experience in the virtual world



Source: Huynh-The, Thien, Quoc-Viet Pham, Xuan-Qui Pham, Thanh Thi Nguyen, Zhu Han, and Dong-Seong Kim (2022). "Artificial Intelligence for the Metaverse: A Survey." arXiv preprint arXiv:2202.10336.

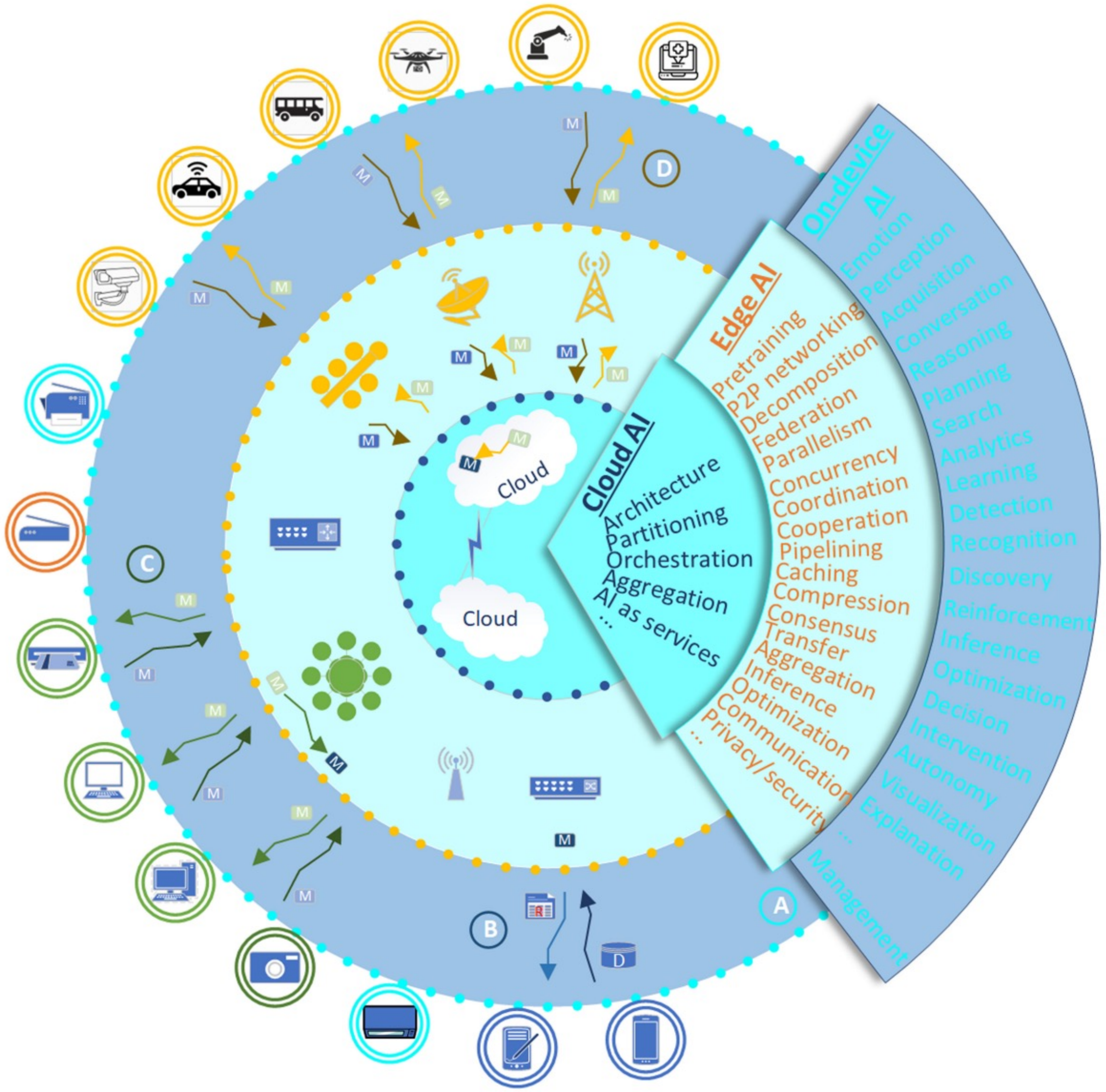
Fusion of AI and Blockchain in Metaverse



Source: Yang, Qinglin, Yetong Zhao, Huawei Huang, Zehui Xiong, Jiawen Kang, and Zibin Zheng (2022). "Fusing blockchain and AI with metaverse: A survey." IEEE Open Journal of the Computer Society 3 : 122-136.

DeAI:

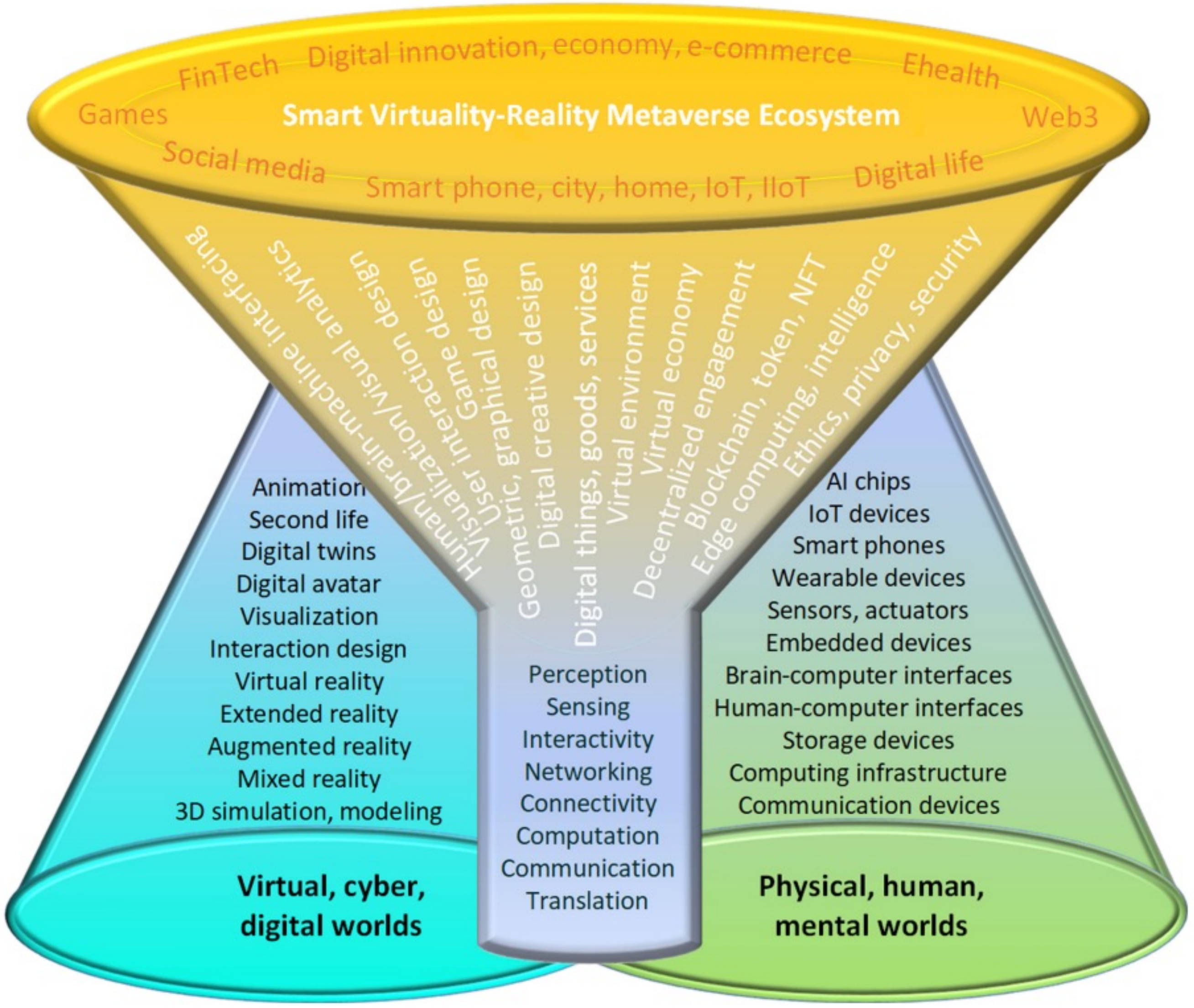
Synthesizing On-device AI, Edge AI, and Cloud AI



Source: Cao, Longbing (2022). "Decentralized ai: Edge intelligence and smart blockchain, metaverse, web3, and desci." IEEE Intelligent Systems 37, no. 3: 6-19.

Smart Virtuality-Reality Metaverse Ecosystem:

Metasynthesizing DeAI, Metaverse, Blockchain, Web3



Source: Cao, Longbing (2022). "Decentralized ai: Edge intelligence and smart blockchain, metaverse, web3, and desci." IEEE Intelligent Systems 37, no. 3: 6-19.

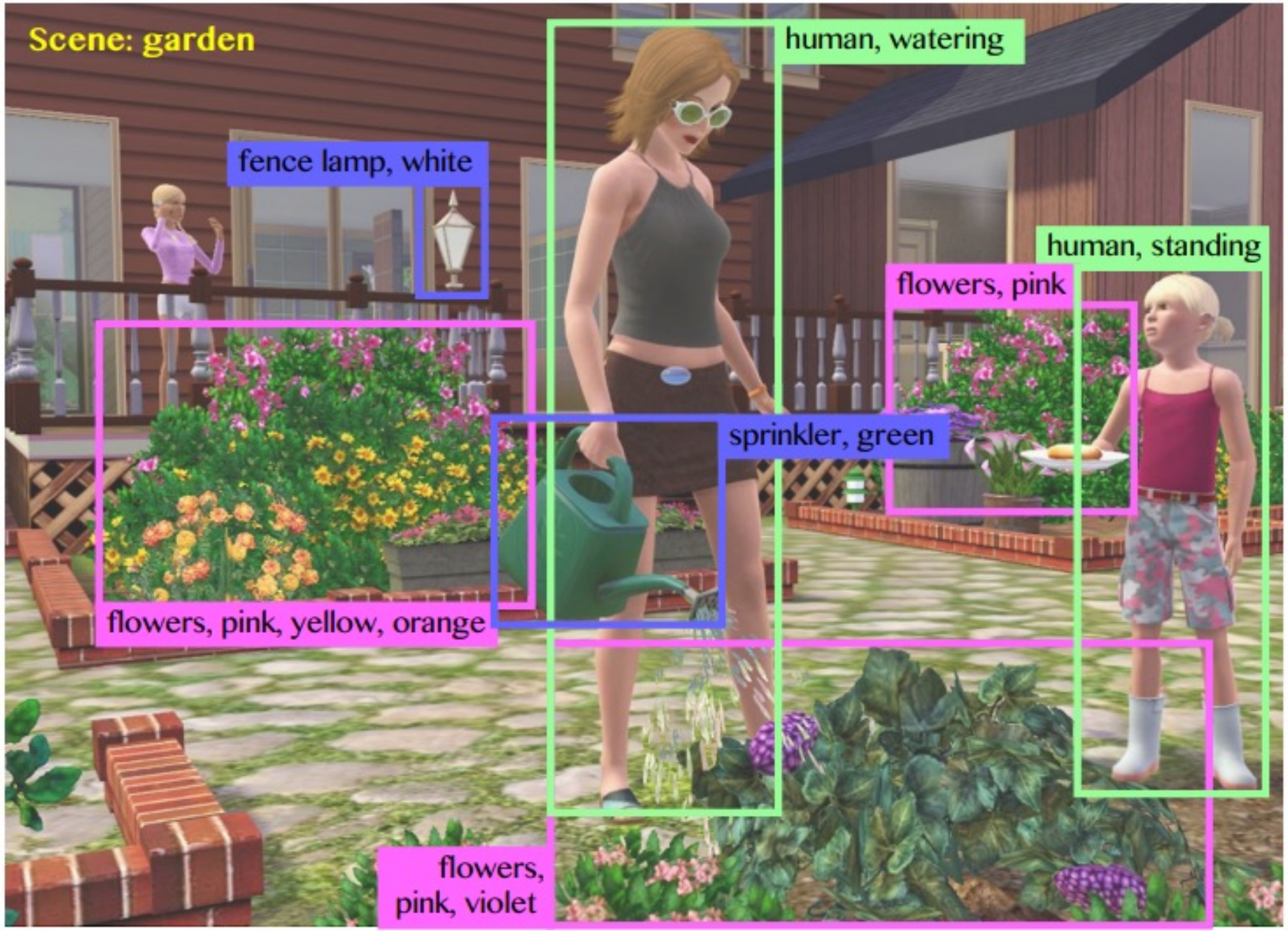
The difference between AR, MR, and VR under the umbrella of XR

XR	VR	MR	AR
Extended Reality	**Virtual Reality**	**Mixed Reality**	**Augmented Reality**
Entire experience spectrum from fully virtual to fully real	User is completely immersed into a virtual world	Environment aware 2D/3D content is overlaid onto the physical space	Non-environment aware 2D/3D content is overlaid onto the physical space

Source: Huynh-The, Thien, Quoc-Viet Pham, Xuan-Qui Pham, Thanh Thi Nguyen, Zhu Han, and Dong-Seong Kim (2022). "Artificial Intelligence for the Metaverse: A Survey." arXiv preprint arXiv:2202.10336.

Computer vision in the metaverse

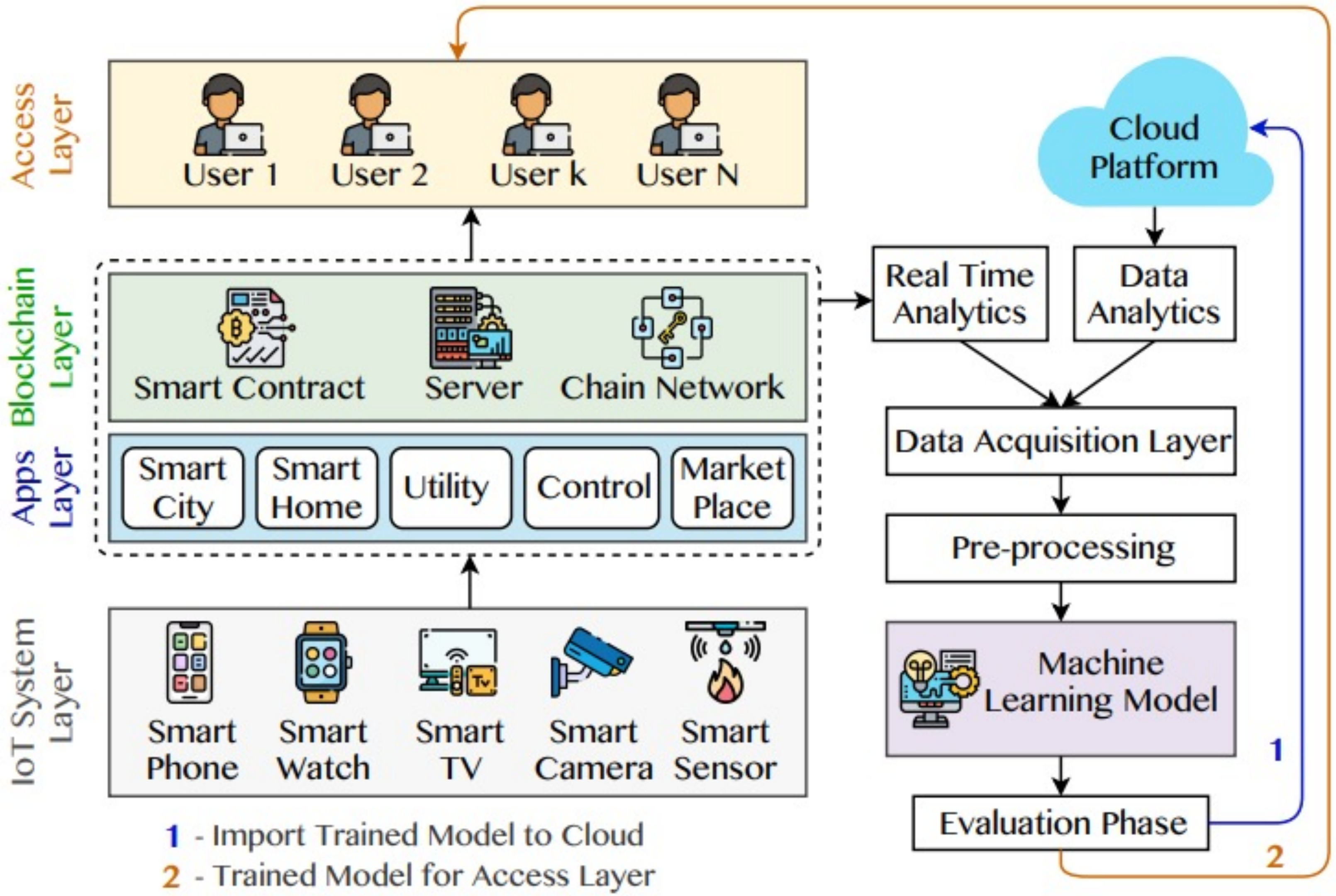
with scene understanding, object detection, and human action/activity recognition



Source: Huynh-The, Thien, Quoc-Viet Pham, Xuan-Qui Pham, Thanh Thi Nguyen, Zhu Han, and Dong-Seong Kim (2022). "Artificial Intelligence for the Metaverse: A Survey." arXiv preprint arXiv:2202.10336.

A Blockchain-based IoT Framework

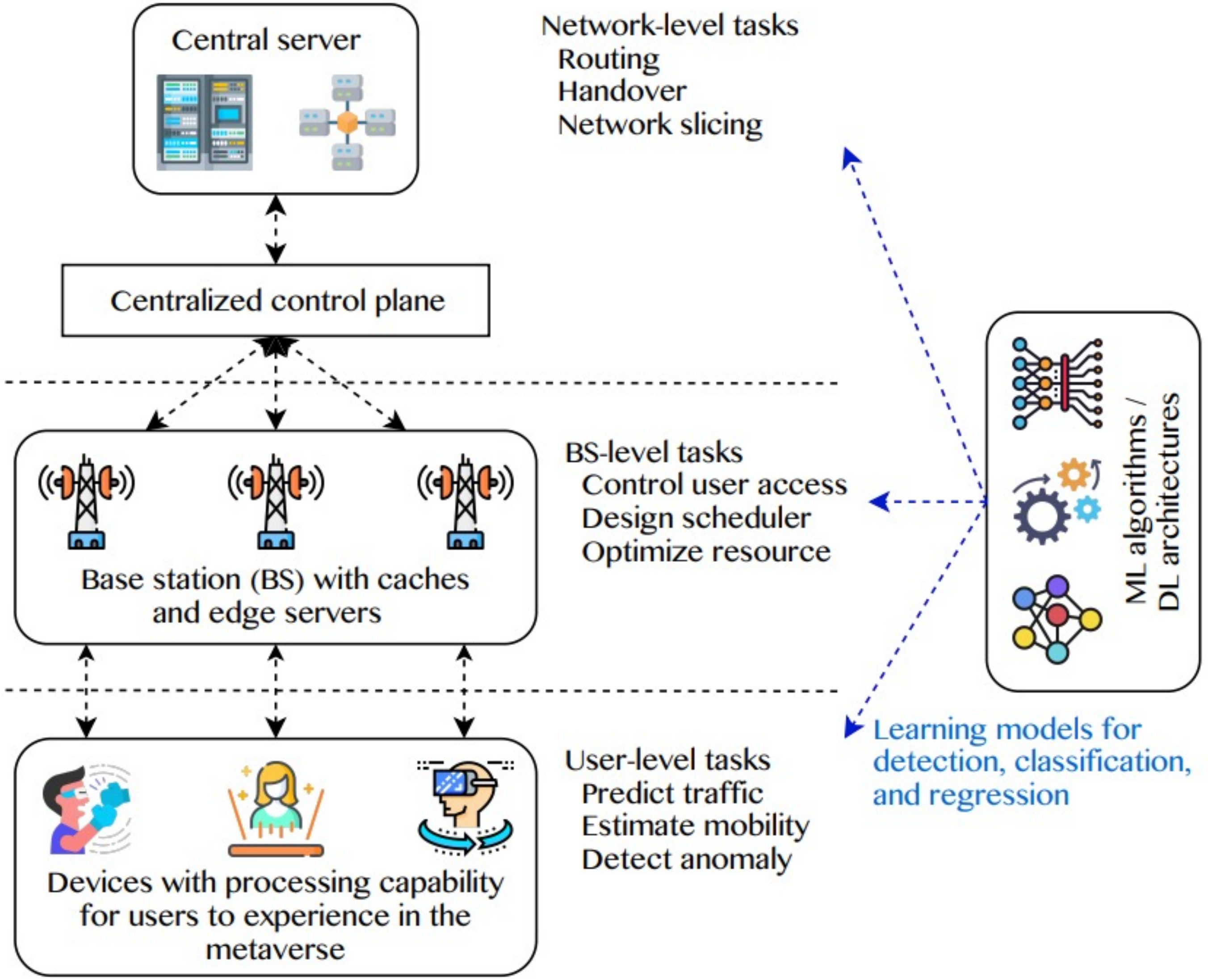
with ML to enhance security and privacy



Source: Huynh-The, Thien, Quoc-Viet Pham, Xuan-Qui Pham, Thanh Thi Nguyen, Zhu Han, and Dong-Seong Kim (2022). "Artificial Intelligence for the Metaverse: A Survey." arXiv preprint arXiv:2202.10336.

5G and beyond for Metaverse Services

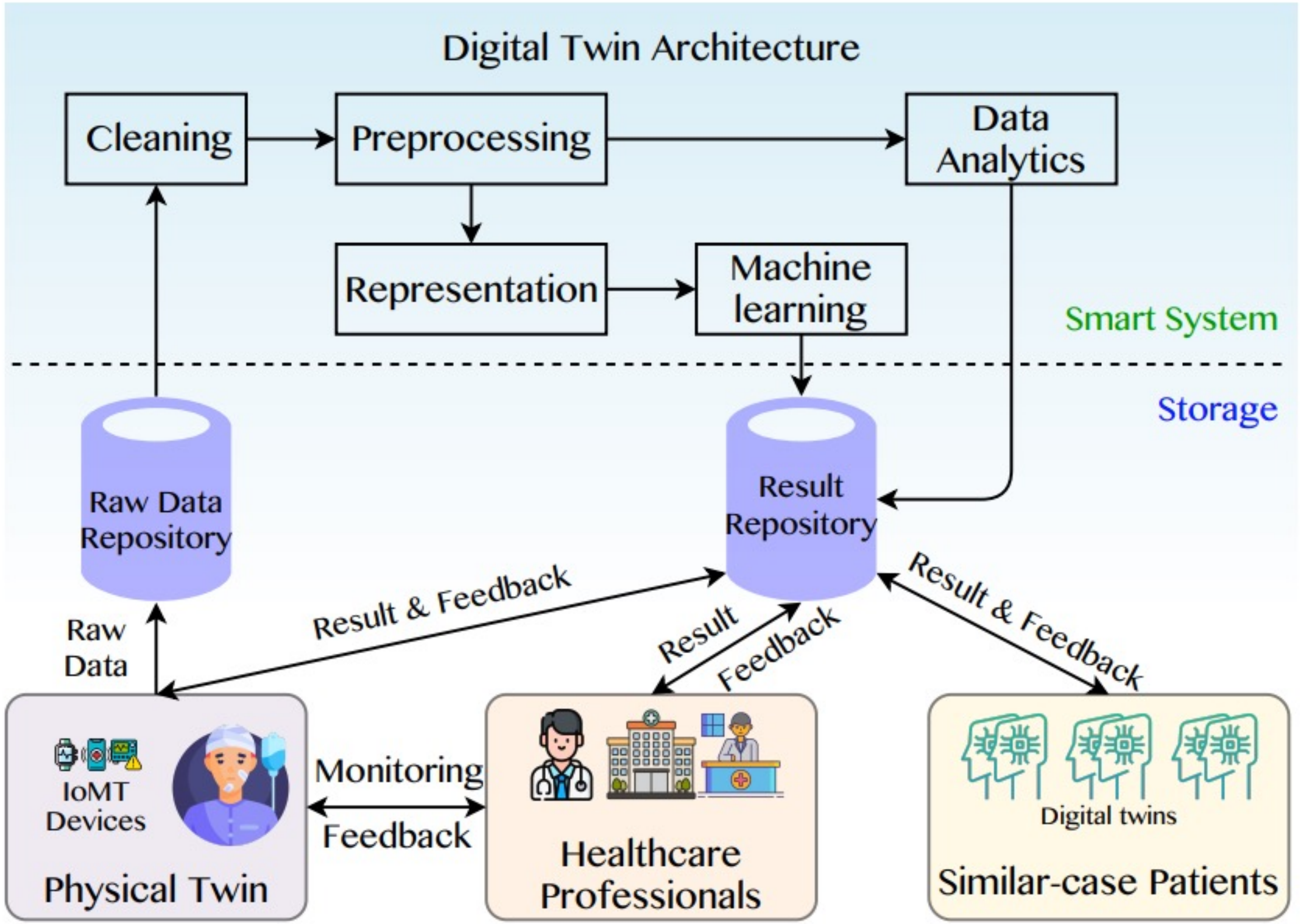
AI with ML algorithms and DL models contribute in multi-level tasks



Source: Huynh-The, Thien, Quoc-Viet Pham, Xuan-Qui Pham, Thanh Thi Nguyen, Zhu Han, and Dong-Seong Kim (2022). "Artificial Intelligence for the Metaverse: A Survey." arXiv preprint arXiv:2202.10336.

A Data-Driven Digital Twin Architecture

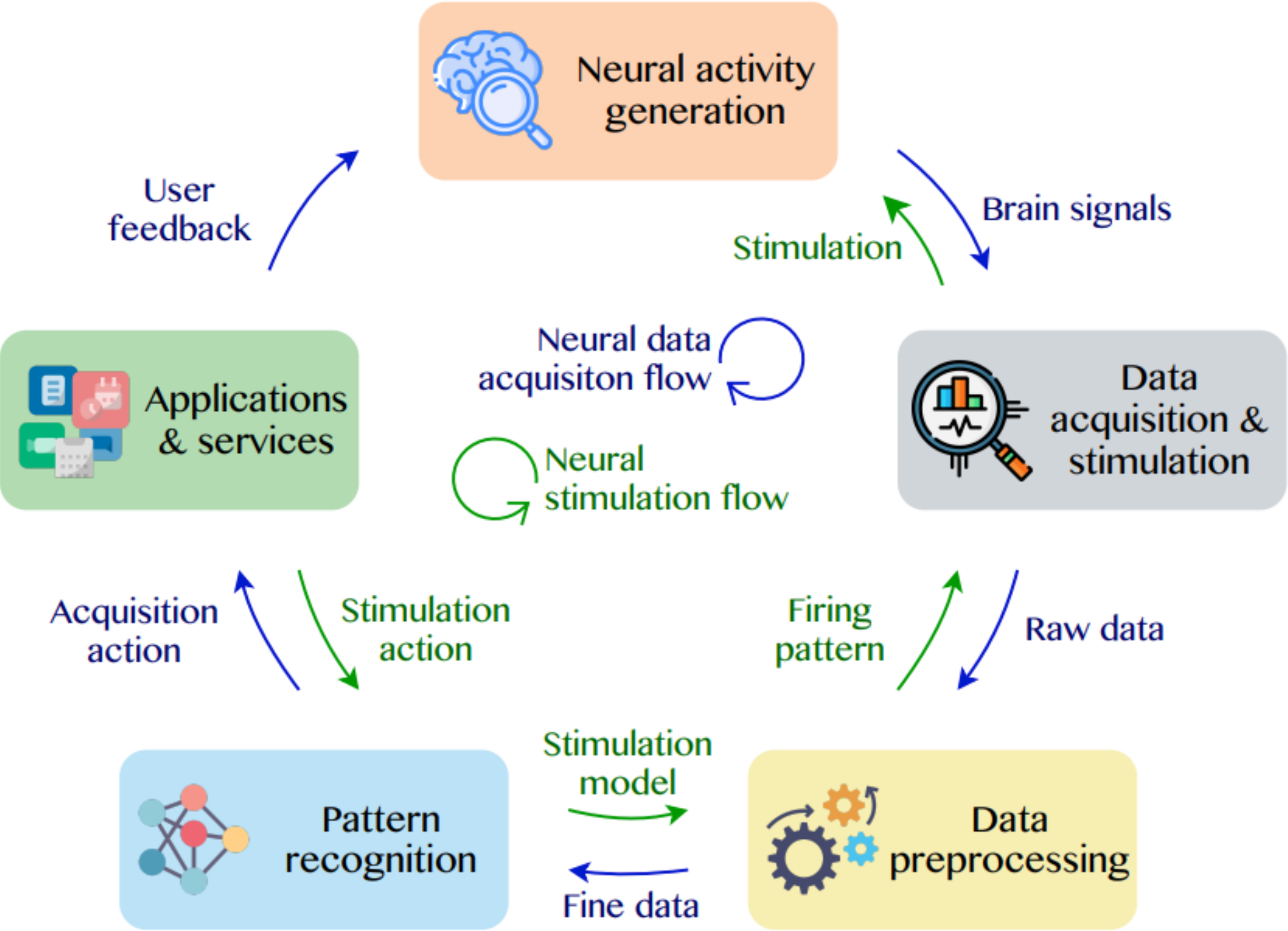
for intelligent healthcare systems using ML to process raw data of IoMedicalThings devices



Source: Huynh-The, Thien, Quoc-Viet Pham, Xuan-Qui Pham, Thanh Thi Nguyen, Zhu Han, and Dong-Seong Kim (2022). "Artificial Intelligence for the Metaverse: A Survey." arXiv preprint arXiv:2202.10336.

Brain-Machine Interfaces (BMIs)

for processing neural signals and responding neural stimulations



Source: Huynh-The, Thien, Quoc-Viet Pham, Xuan-Qui Pham, Thanh Thi Nguyen, Zhu Han, and Dong-Seong Kim (2022). "Artificial Intelligence for the Metaverse: A Survey." arXiv preprint arXiv:2202.10336.

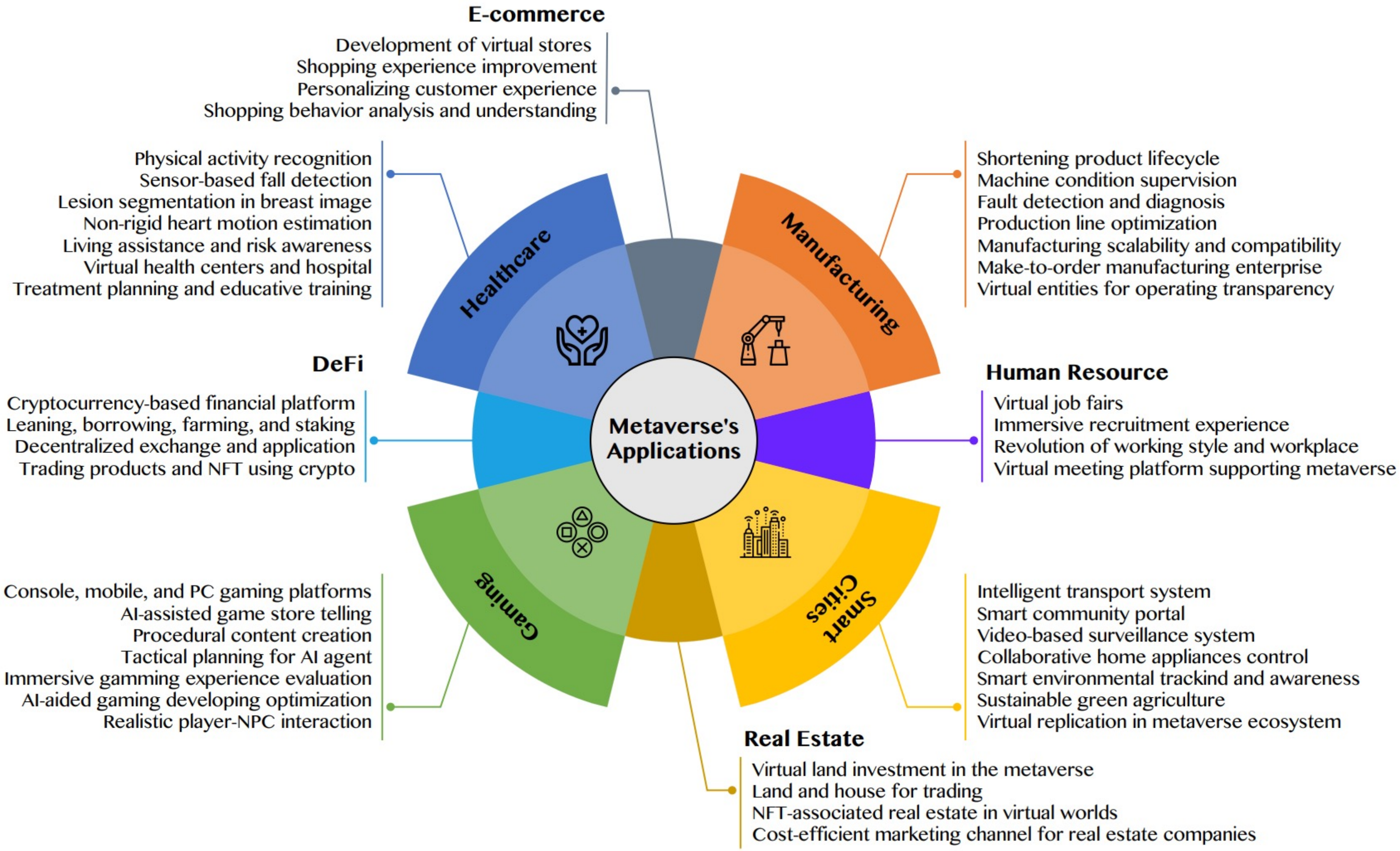
AI for the Metaverse

Technical Aspect	Ref	Task	AI Technique
NLP	[20]	Word and linguistic prediction for language modeling.	RNNs and LSTM networks with the attention mechanisms.
	[21]		Advanced memory network with residual connection.
	[24]		Deep networks with gated connection and bi-directional structure.
	[25]	Analyzing and understand the representation of words from characters	General deep networks with CNN and LSTM architectures.
	[27]	Identifying prefixes and suffixes and detecting mis-spelled words	DL framework with CNN, Bi-LSTM, and conditional random field.
	[29]	Sentiment prediction and question type classifica-tion.	Various CNNs and LSTM networks with simple structures and advanced-designed architectures.
	[31]	Generate short text in image captioning and long text in virtual question answer.	DL framework with single RNN/LSTM and mixture LSTM-CNN models.
	[32]	Semantic labeling, context retrieval, and language interpretation.	Unsupervised and reinforcement learning with common RNN/LSTM and CNN models.

Source: Huynh-The, Thien, Quoc-Viet Pham, Xuan-Qui Pham, Thanh Thi Nguyen, Zhu Han, and Dong-Seong Kim (2022). "Artificial Intelligence for the Metaverse: A Survey." arXiv preprint arXiv:2202.10336.

AI for the Metaverse in the Application Aspects

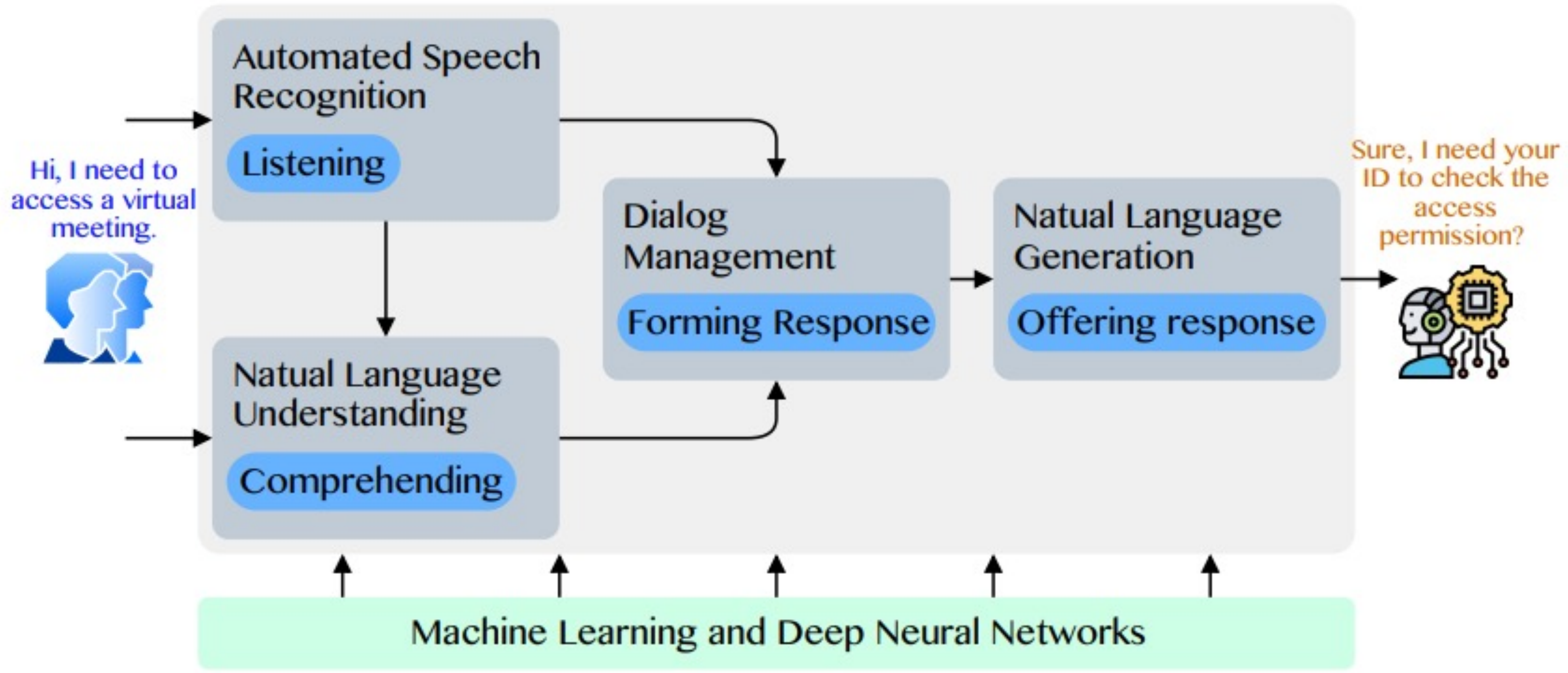
healthcare, manufacturing, smart cities, gaming
E-commerce, human resources, real estate, and DeFi



Source: Huynh-The, Thien, Quoc-Viet Pham, Xuan-Qui Pham, Thanh Thi Nguyen, Zhu Han, and Dong-Seong Kim (2022). "Artificial Intelligence for the Metaverse: A Survey." arXiv preprint arXiv:2202.10336.

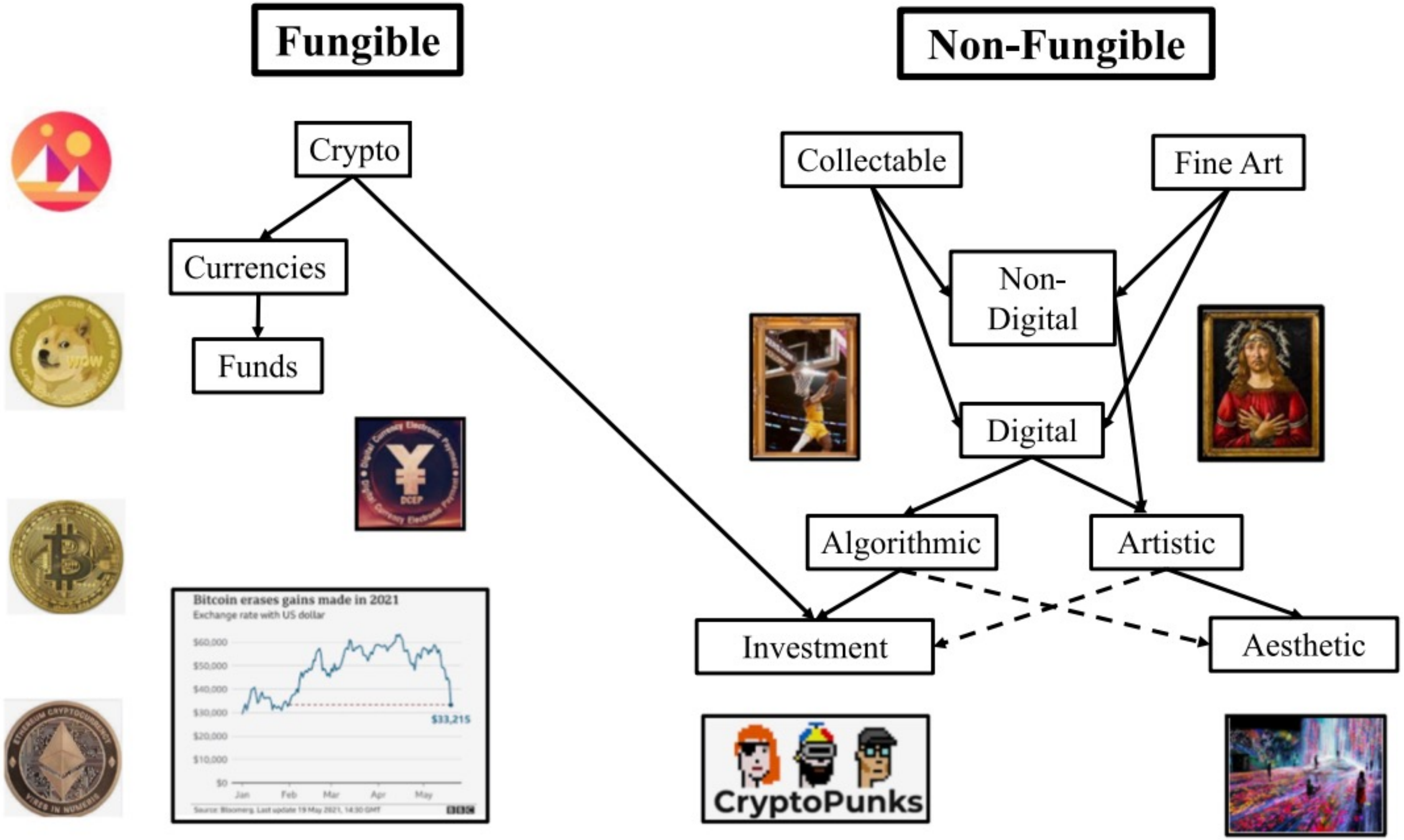
Conversational AI

to deliver contextual and personal experience to users



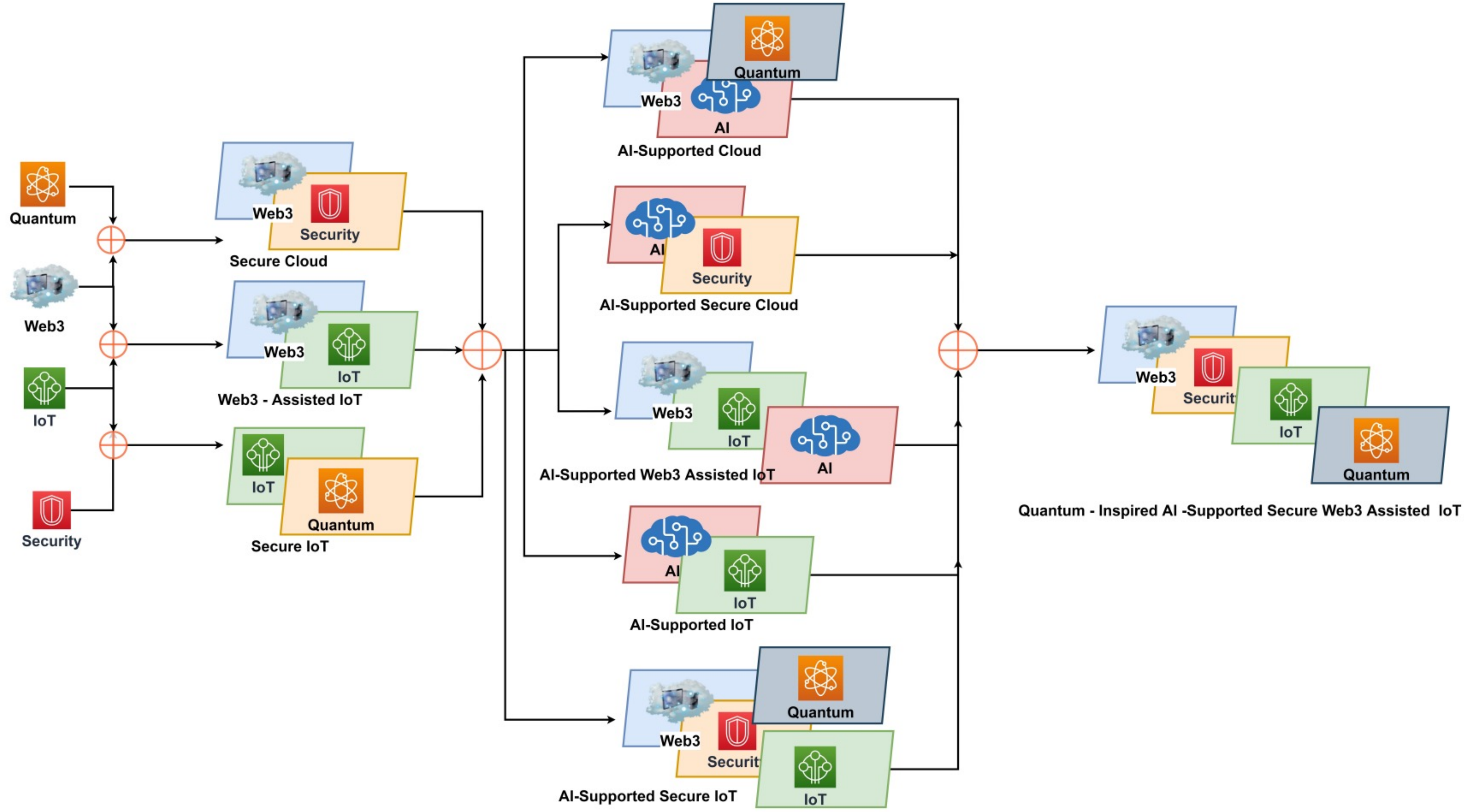
Source: Huynh-The, Thien, Quoc-Viet Pham, Xuan-Qui Pham, Thanh Thi Nguyen, Zhu Han, and Dong-Seong Kim (2022). "Artificial Intelligence for the Metaverse: A Survey." arXiv preprint arXiv:2202.10336.

Blockchain-Registered: Crypto, Collectables, and Art.



Source: Belk, Russell, Mariam Humayun, and Myriam Brouard. (2022)
"Money, possessions, and ownership in the Metaverse: NFTs, cryptocurrencies, Web3 and Wild Markets." Journal of Business Research 153: 198-205.

Combination of Web3 with other Technologies



Source: Sheridan, Dan, James Harris, Frank Wear, Jerry Cowell Jr, Easton Wong, and Abbas Yazdinejad. (2022) "Web3 Challenges and Opportunities for the Market." arXiv preprint arXiv:2209.02446.

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/

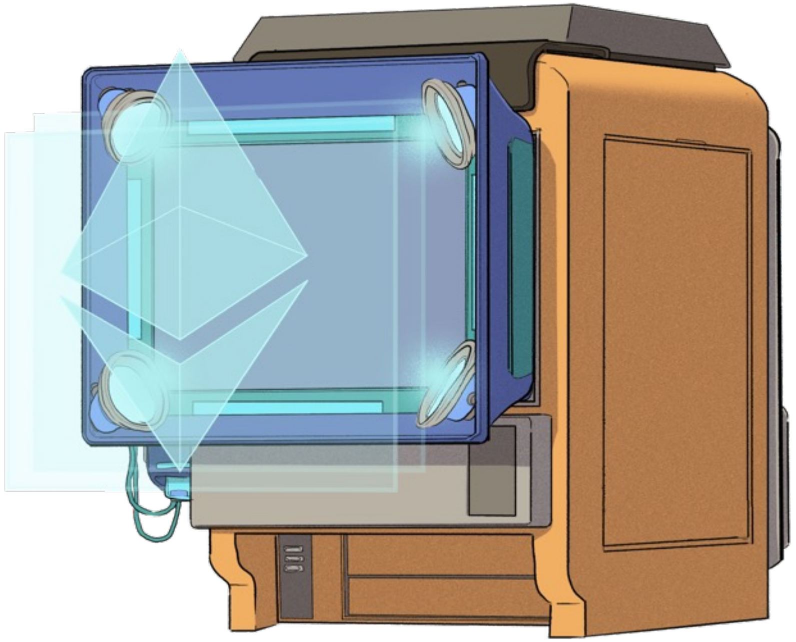
(DeFi)
Decentralized Applications (Dapps)

- **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

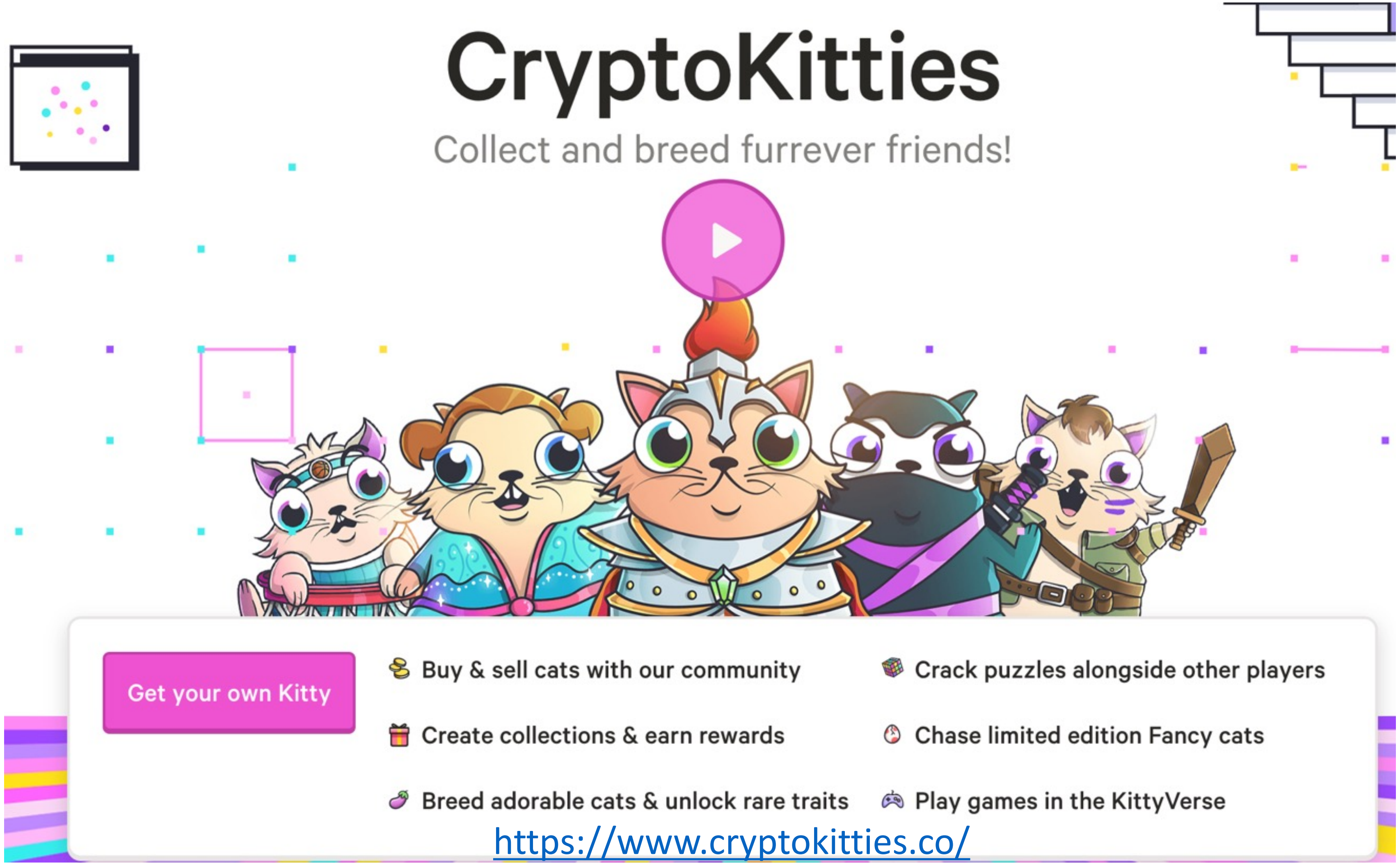
- **Ethereum** isn't just for **digital money**.
- Anything you can own can be **represented**, **traded** and **put to use** as **non-fungible tokens (NFTs)**.



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

Non-Fungible Tokens (NFT)

CryptoKitties



https://www.cryptokitties.co/

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

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**

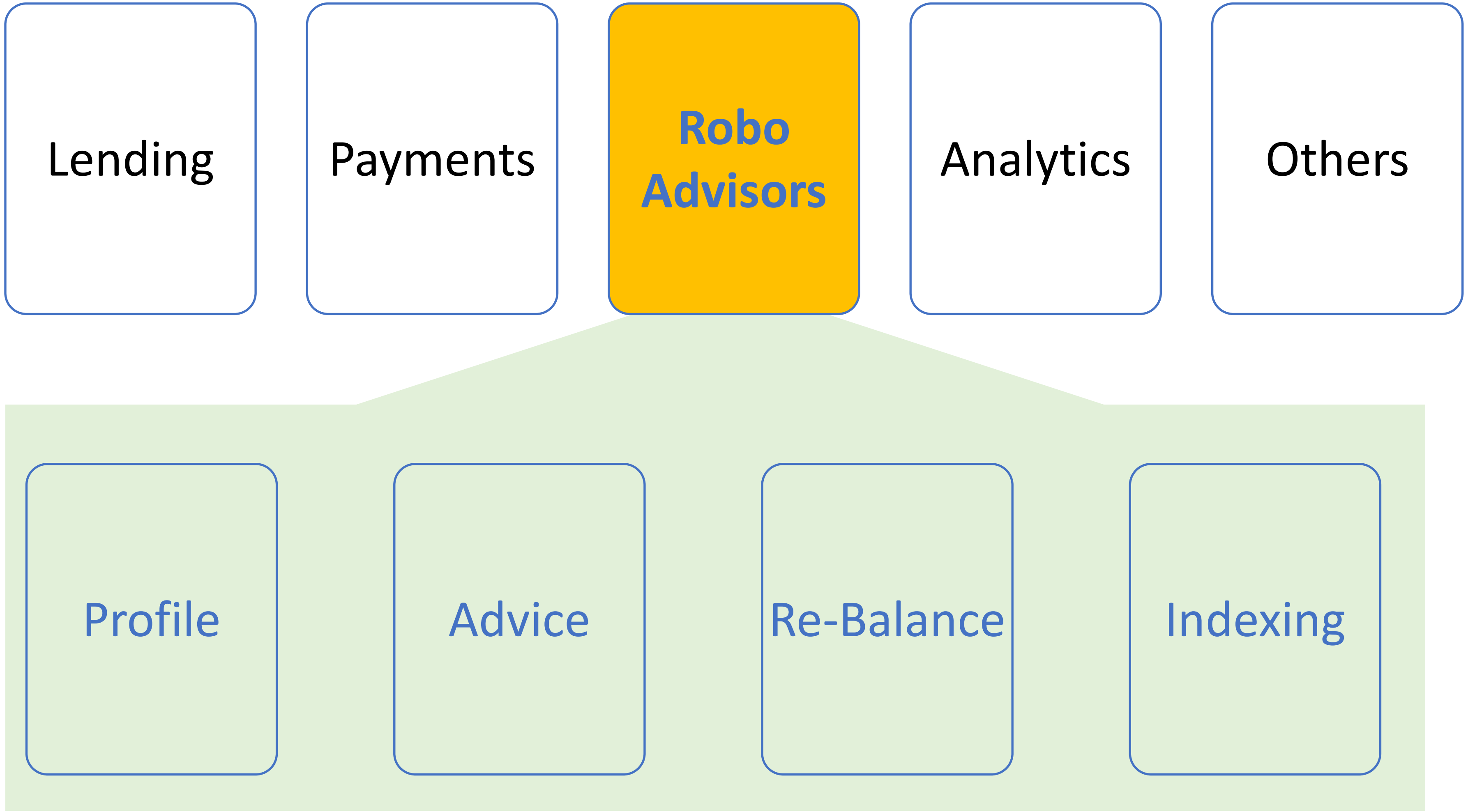
Source: Parma Bains, Mohamed Diaby, Dimitris Drakopoulos, Julia Faltermeier, Federico Grinberg, Evan Papageorgiou, Dmitri Petrov, Patrick Schneider, and Nobu Sugimoto (2021), The Crypto Ecosystem and Financial Stability Challenges, International Monetary Fund, October 2021

Financial Services

Technology Innovation

FinTech Innovation

FinTech high-level classification

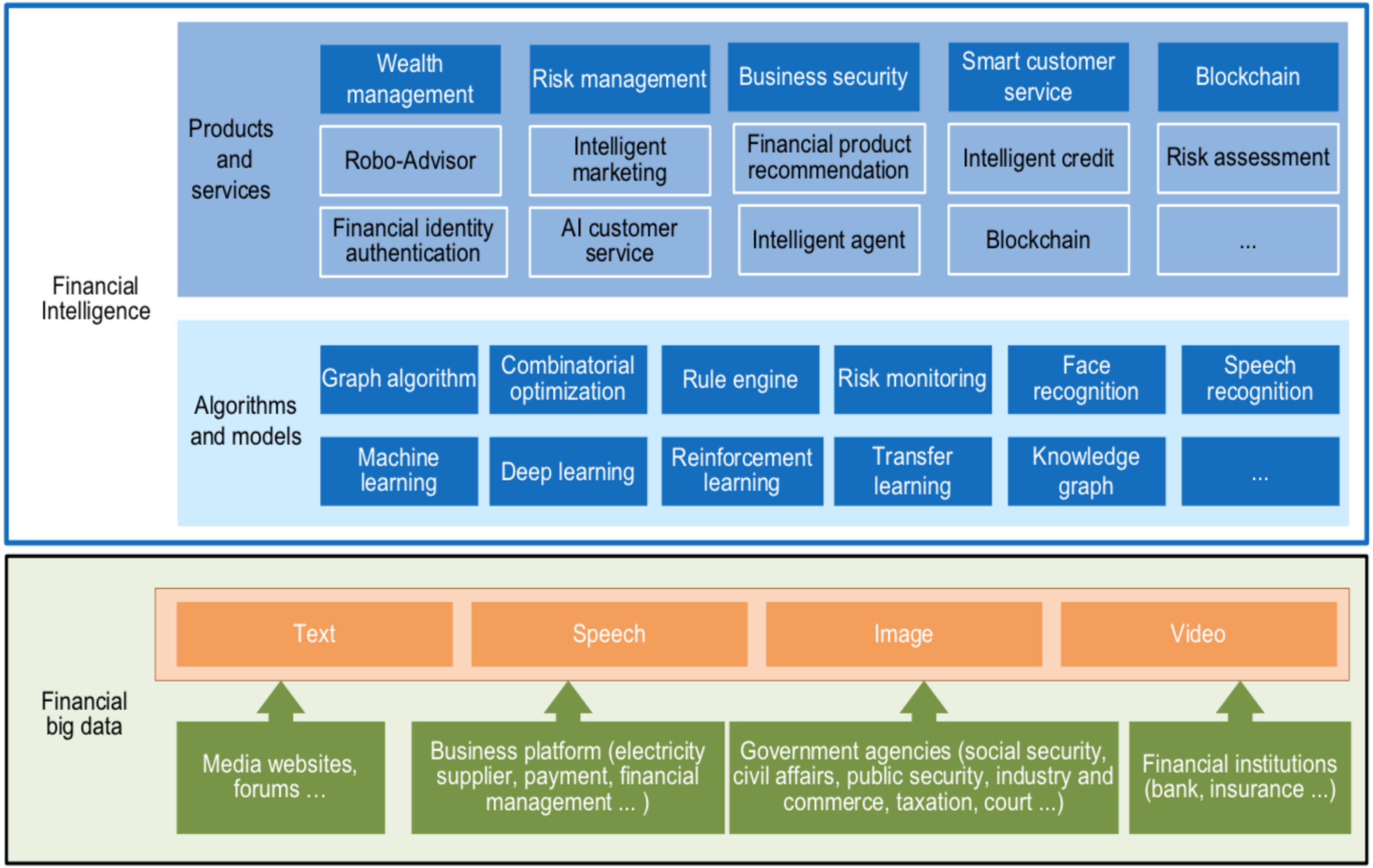


Source: Paolo Sironi (2016), “FinTech Innovation: From Robo-Advisors to Goal Based Investing and Gamification”, Wiley.

Technology-driven Financial Industry Development

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

AI 2.0

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

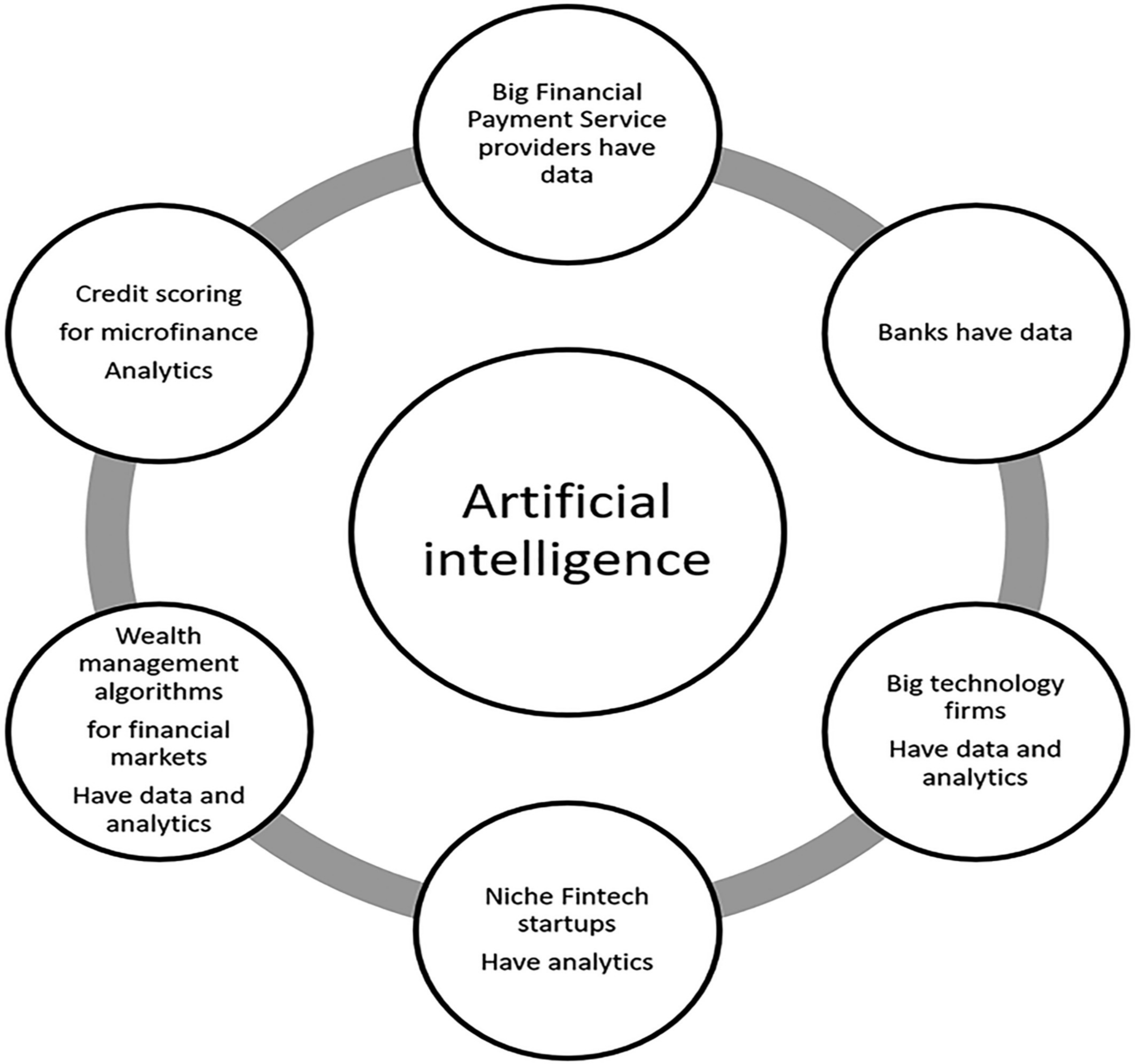
Yunhe Pan (2016), "Heading toward artificial intelligence 2.0." Engineering 2, no. 4, 409-413.

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

Artificial Intelligence in the Financial Markets



Source: Ashta, Arvind, and Heinz Herrmann (2021). "Artificial intelligence and fintech: An overview of opportunities and risks for banking, investments, and microfinance." Strategic Change 30, no. 3 (2021): 211-222.

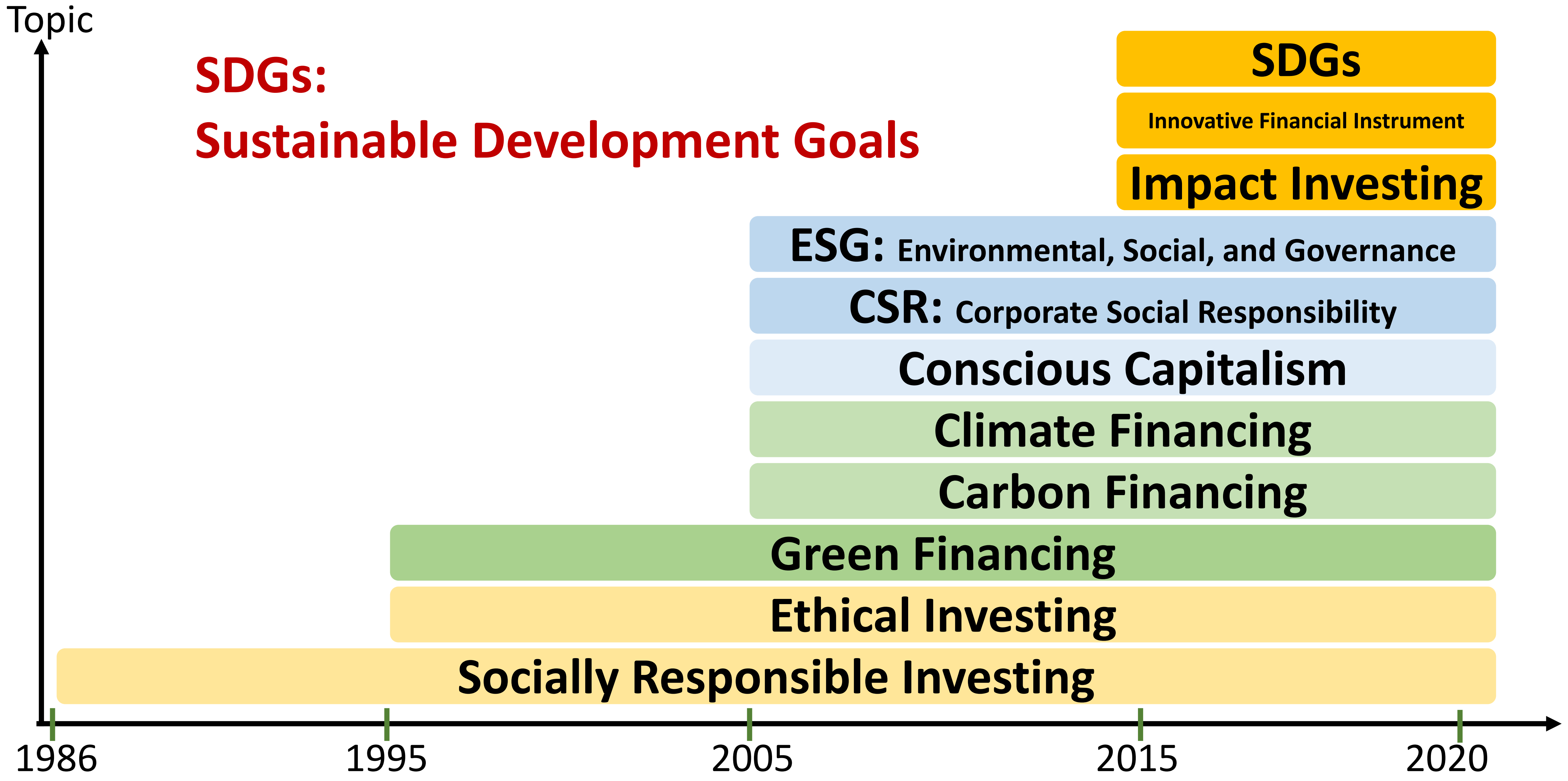
AI in Managerial Blind Spots:
Unknown Knowns and Unknown Unknowns

Do I know whether I know?		Do I know? Yes	Do I know? No
	Yes	ERP, CRM, MIS, Transaction Processing Systems	Data Science & Business Intelligence
	No	Data Mining & Supervised Machine Learning	Big Data & Unsupervised Machine Learning

Source: Ashta, Arvind, and Heinz Herrmann (2021). "Artificial intelligence and fintech: An overview of opportunities and risks for banking, investments, and microfinance." Strategic Change 30, no. 3 (2021): 211-222.

Green Finance
and
Sustainable Finance

Evolution of Sustainable Finance Research



Source: Kumar, S., Sharma, D., Rao, S., Lim, W. M., & Mangla, S. K. (2022). Past, present, and future of sustainable finance: Insights from big data analytics through machine learning of scholarly research. Annals of Operations Research, 1-44.

AI for Environmental, Social, and Governance (AI4ESG)

Source: Nenad Tomašev, Julien Cornebise, Frank Hutter, Shakir Mohamed, Angela Picciariello, Bec Connelly, Danielle Belgrave et al. (2020) "AI for social good: unlocking the opportunity for positive impact." Nature Communications 11, no. 1: 1-6.

AI for Social Good (AI4SG)

Source: Nenad Tomašev, Julien Cornebise, Frank Hutter, Shakir Mohamed, Angela Picciariello, Bec Connelly, Danielle Belgrave et al. (2020) "AI for social good: unlocking the opportunity for positive impact." Nature Communications 11, no. 1: 1-6.

Sustainability

SDGs

CSR

ESG

Sustainable Development Goals (SDGs)

Source: https://sdgs.un.org/goals

Sustainable Development Goals (SDGs) and 5P

Partnership

Peace

Prosperity

People

Planet

Source: Folke, Carl, Reinette Biggs, Albert V. Norström, Belinda Reyers, and Johan Rockström. "Social-ecological resilience and biosphere-based sustainability science."Ecology and Society 21, no. 3 (2016).

Green Finance

Generic term
implying use or diversion
of financial resources
to deploy and support projects
with long term positive impact
on the environment

Source: Bhattacharyya, Rupsha. "Green finance for energy transition, climate action and sustainable development: overview of concepts, applications, implementation and challenges." Green Finance 4, no. 1 (2022): 1-35.

Sustainable Finance

Finances

deployed in support of projects that ensure just, sustainable and inclusive growth or attainment of one or more sustainable development goals

Source: Bhattacharyya, Rupsha. "Green finance for energy transition, climate action and sustainable development: overview of concepts, applications, implementation and challenges." Green Finance 4, no. 1 (2022): 1-35.

Carbon Finance

Financial instruments
based on
economic value of carbon emissions
which an organization cannot avoid but which
it offsets by funding other compensatory projects
that contribute to carbon emissions reduction

Source: Bhattacharyya, Rupsha. "Green finance for energy transition, climate action and sustainable development: overview of concepts, applications, implementation and challenges." Green Finance 4, no. 1 (2022): 1-35.

Climate Finance

Finances deployed
in support of low carbon and
climate resilient projects
that help in climate change mitigation and
adaptation efforts,
particularly in the
energy and infrastructure sectors

Source: Bhattacharyya, Rupsha. "Green finance for energy transition, climate action and sustainable development: overview of concepts, applications, implementation and challenges." Green Finance 4, no. 1 (2022): 1-35.

ESG Investing

Investments considering the broad range of
environmental (e.g. climate change,
pollution biodiversity loss),
social (e.g. working conditions, human rights, salary or
compensation structures)
and governance (e.g. board composition, diversity and
inclusion, taxes)
characteristics of the projects or companies being invested in;
ethical and business sustainability considerations are
integral part of financing

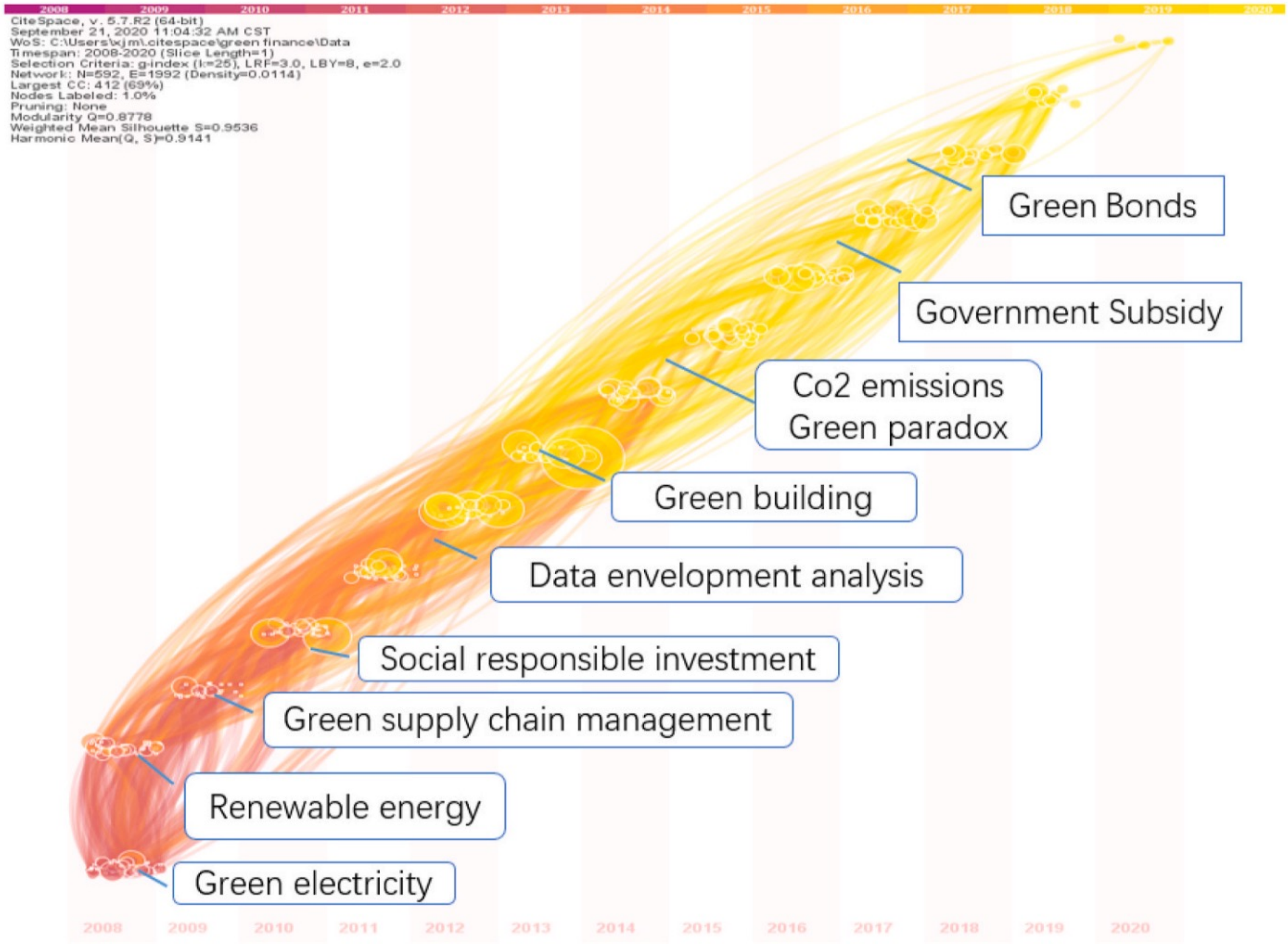
Source: Bhattacharyya, Rupsha. "Green finance for energy transition, climate action and sustainable development: overview of concepts, applications, implementation and challenges." Green Finance 4, no. 1 (2022): 1-35.

Impact Investing

Investing in projects
that solve a social or environmental problem;
the focus is on the positive impact
rather than the
means used to produce that impact

Source: Bhattacharyya, Rupsha. "Green finance for energy transition, climate action and sustainable development: overview of concepts, applications, implementation and challenges." Green Finance 4, no. 1 (2022): 1-35.

Dynamic Trends of Green Finance and Energy Policy



Source: Wang, Moran, Xuerong Li, and Shouyang Wang. (2021) "Discovering research trends and opportunities of green finance and energy policy: A data-driven scientometric analysis." Energy Policy 154 (2021): 112295.

ESG:

Environmental

Social

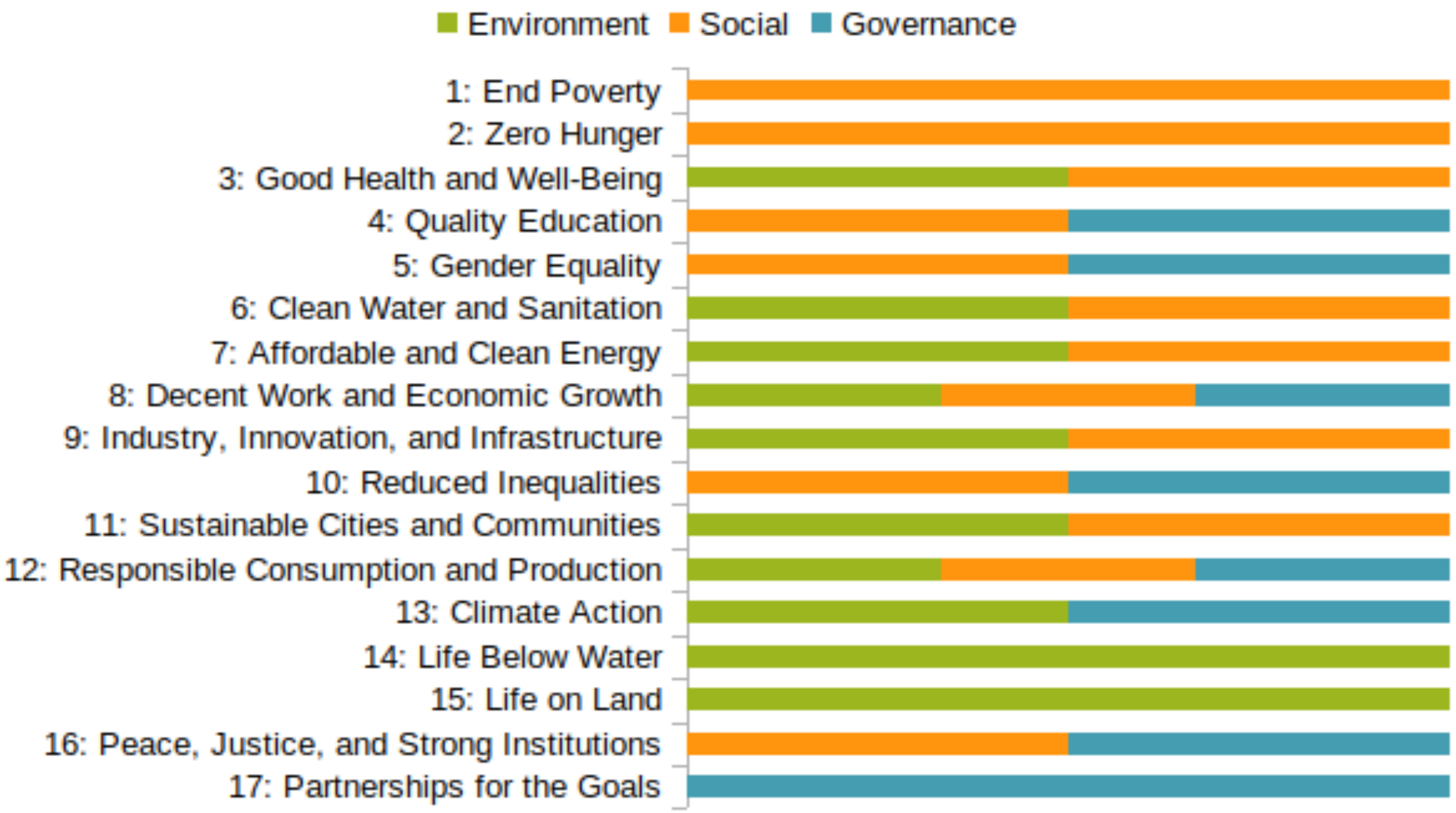
Governance

CSR:
Corporate
Social
Responsibility

ESG to 17 SDGs

Source: Henrik Skaug Sætra (2021) "A Framework for Evaluating and Disclosing the ESG Related Impacts of AI with the SDGs." Sustainability 13, no. 15 (2021): 8503.

ESG to 17 SDGs



Source: https://sustainometric.com/esg-to-sdgs-connected-paths-to-a-sustainable-future/

Generative AI for ESG Applications

AI and Sustainability Development Goals (SDGs)

SDGs	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	No poverty	Zero hunger	Good health and well-being	Quality education	Gender equality	Clean water and sanitation	Affordable and clean energy	Decent work and economic growth	Industry, innovation and infrastructure	Reduces inequalities	Sustainable cities and communities	Responsible consumption and production	Climate action	Life below water	Life on land	Peace, justice and strong institutions	Partnerships for the goals
Economic								●	●	●	○						●
Ecological		○					○				○	○	●	●	●		
Social	●	●	●	●	●	●	●				●	●				●	
Positive impact of AI*	100%	76%	69%	10%0	56%	100%	100%	92%	100%	90%	100%	82%	80%	90%	100%	58%	26%

Note: ● adopted from Vinuesa et al. (2020), ○ added based on our analysis.
*The assessment of AI's possible positive impact is based on a consensus-based expert elicitation process (Vinuesa et al., 2020).

Source: Schoormann, T., Strobel, G., Möller, F., Petrik, D., & Zschech, P. (2023).
Artificial Intelligence for Sustainability—A Systematic Review of Information Systems Literature. Communications of the Association for Information Systems, 52(1), 8.

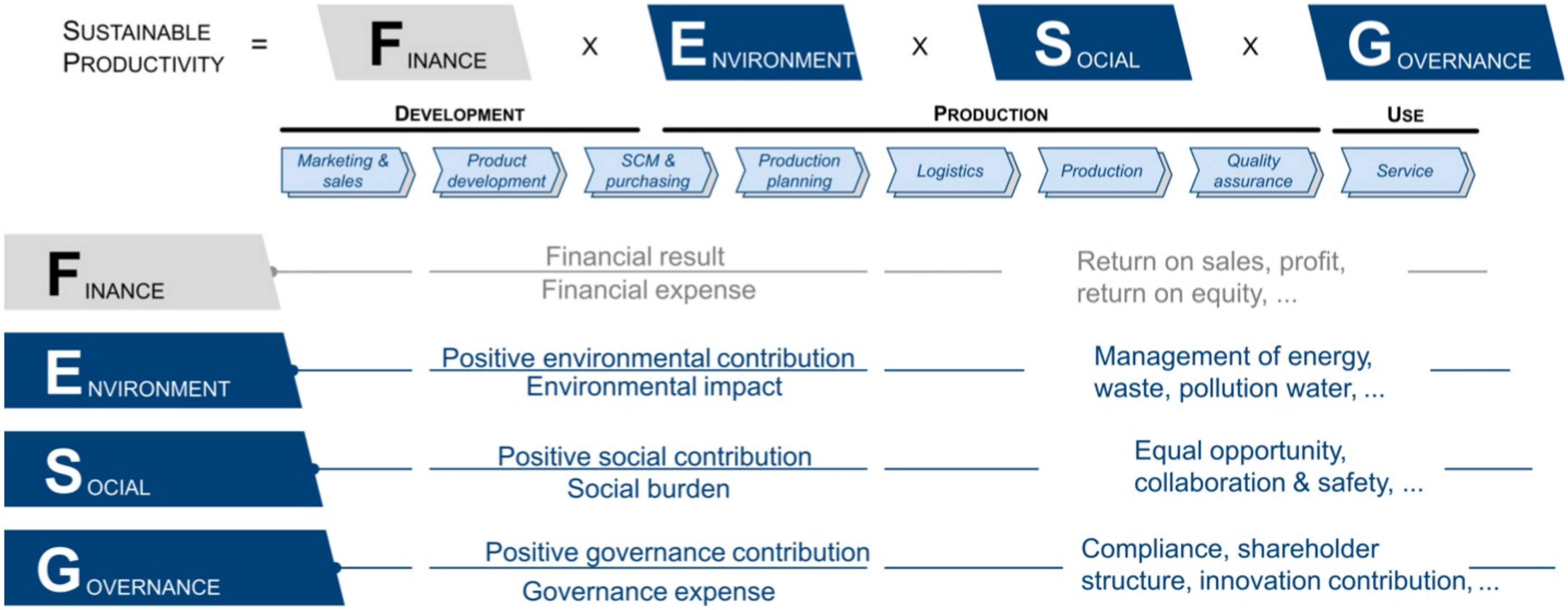
AI for Sustainability

Dimension	Code characteristics					
Primary objective[1]	Develop new (AI) methods *(11/95)*	Compare (AI) methods *(39/95)*	Apply (AI) methods *(53/95)*	Develop new system *(20/95)*	Other objective *(4/95)*	
Sustainability dimension	Economic *(23/95)*	Ecological *(17/95)*	Social *(72/95)*			
Sustainable Development Goals (SDGs)	SDG 1 *(0/95)*	SDG 2 *(2/95)*	SDG 3 *(55/95)*	SDG 4 *(6/95)*	SDG 5 *(0/95)*	SDG 6 *(0/95)*
	SDG 7 *(9/95)*	SDG 8 *(7/95)*	SDG 9 *(8/95)*	SDG 10 *(1/95)*	SDG 11 *(9/95)*	SDG 12 *(8/95)*
	SDG 13 *(2/95)*	SDG 14 *(0/95)*	SDG 15 *(2/95)*	SDG 16 *(11/95)*	SDG 17 *(0/95)*	
Data source	Reviews *(12/95)*	Social media/ Online forums *(31/95)*	Health records *(21/95)*	Environment/ Weather *(10/95)*	Energy *(5/95)*	
Data source plurality	Single source *(50/95)*	Multiple sources *(44/95)*	N/A *(1/95)*			
Data sensitivity	Publicly available data *(64/95)*	Internal data *(16/95)*	Other *(11/95)*	N/A *(9/95)*		
Manual labeling	Yes *(32/95)*	No *(63/95)*				
Technology	ML *(91/95)*	NLP *(42/95)*	CV *(12/95)*	Other *(21/95)*		
Type of learning for ML approach	Supervised learning *(85/95)*	Unsupervised learning *(23/95)*				
Neural vs. non-neural	Non-neural *(45/95)*	Neural *(50/95)*	Deep learning *(38/95)*			
Evaluation	Technical evaluation *(83/95)*	Domain evaluation *(25/95)*				
Paradigm	DSR/ADR *(30/95)*	Non-DSR/ADR *(64/95)*				
	0-9	10-29	30-54	55-69	70-95	

Notes: Code dimensions are not mutually exclusive; one article can be classified into one or more code characteristics; [1] 'Compare' does include 'apply'.

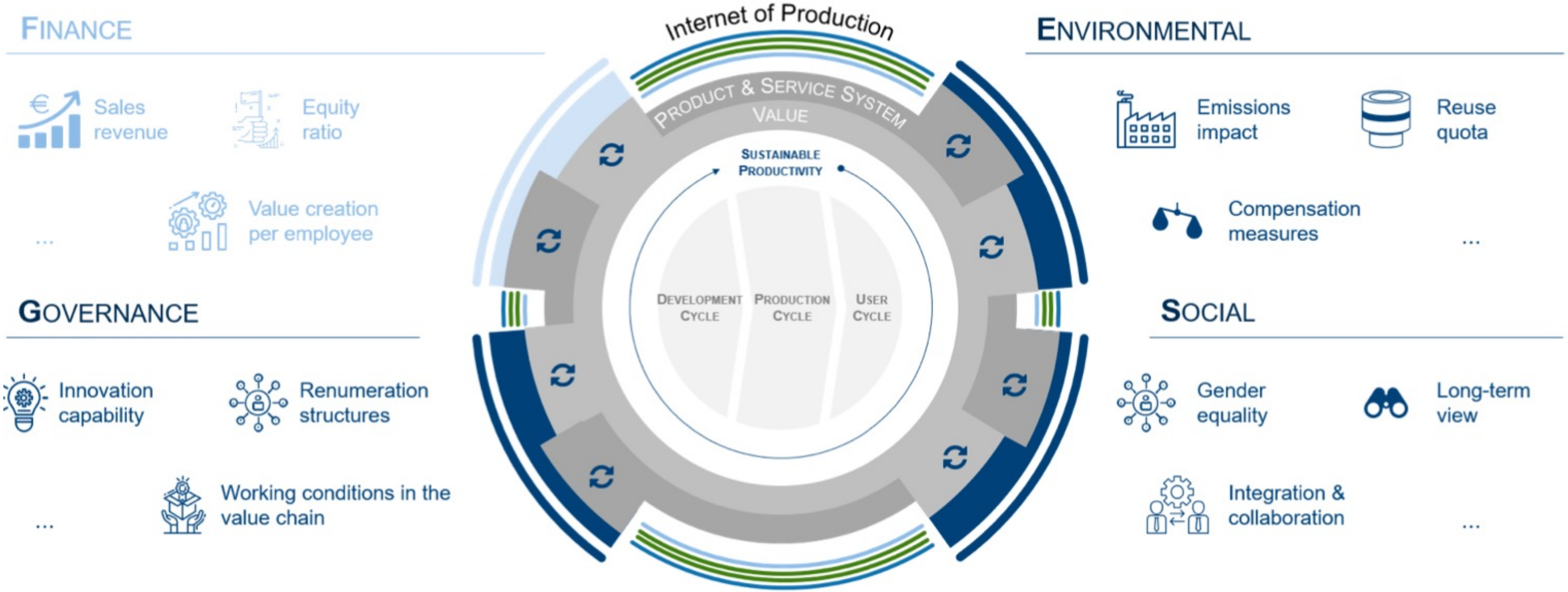
Source: Schoormann, T., Strobel, G., Möller, F., Petrik, D., & Zschech, P. (2023).
Artificial Intelligence for Sustainability—A Systematic Review of Information Systems Literature. Communications of the Association for Information Systems, 52(1), 8.

Sustainable Productivity: Finance ESG



Source: Huang, Ziqi, Yang Shen, Jiayi Li, Marcel Fey, and Christian Brecher (2021). "A survey on AI-driven digital twins in Industry 4.0: Smart manufacturing and advanced robotics." Sensors 21, no. 19: 6340.

Sustainable Resilient Manufacturing ESG

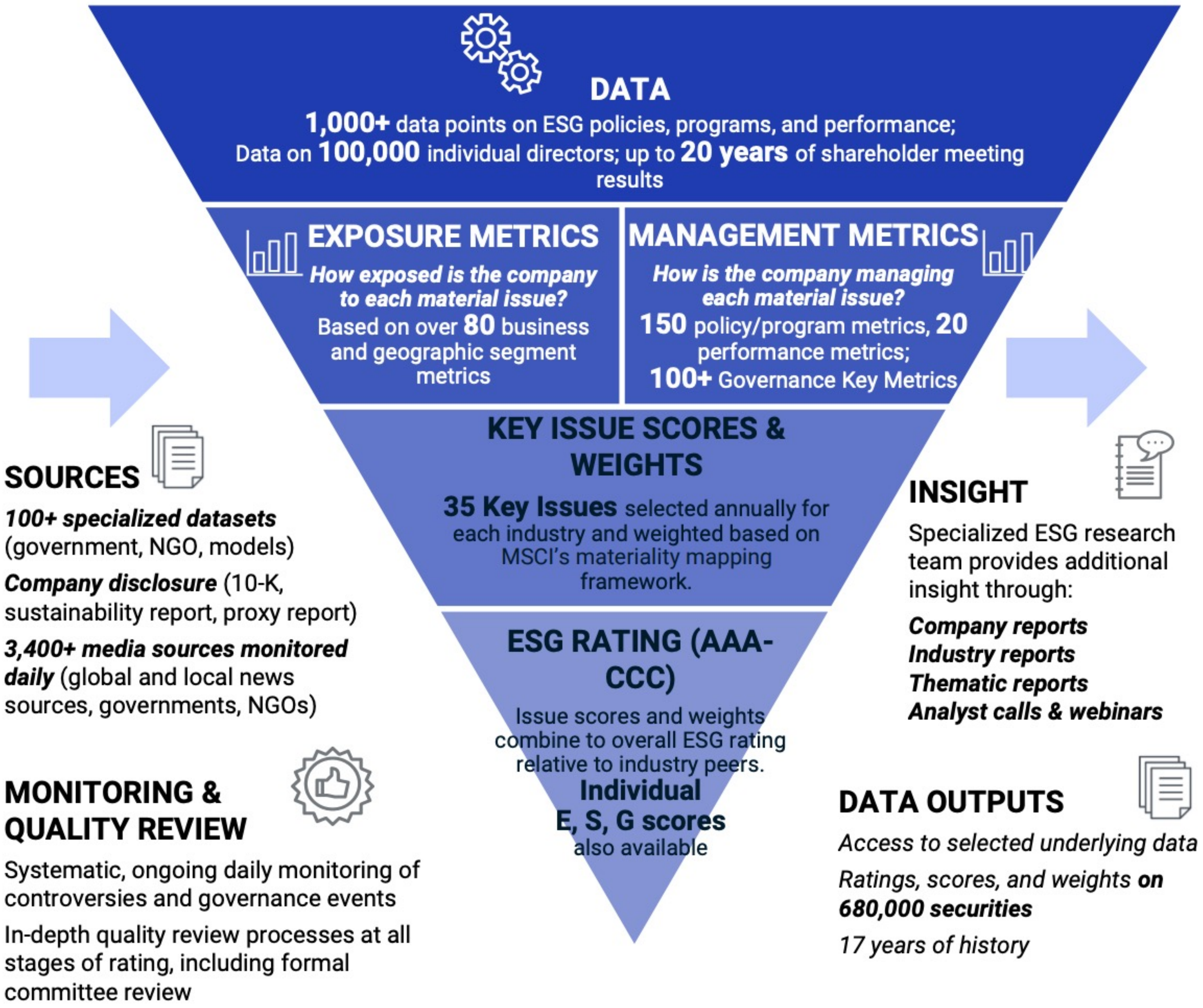


Source: Huang, Ziqi, Yang Shen, Jiayi Li, Marcel Fey, and Christian Brecher (2021). "A survey on AI-driven digital twins in Industry 4.0: Smart manufacturing and advanced robotics." Sensors 21, no. 19: 6340.

ESG Indexes

- MSCI ESG Index
- Dow Jones Sustainability Indices (DJSI)
- FTSE ESG Index

MSCI ESG Rating Framework



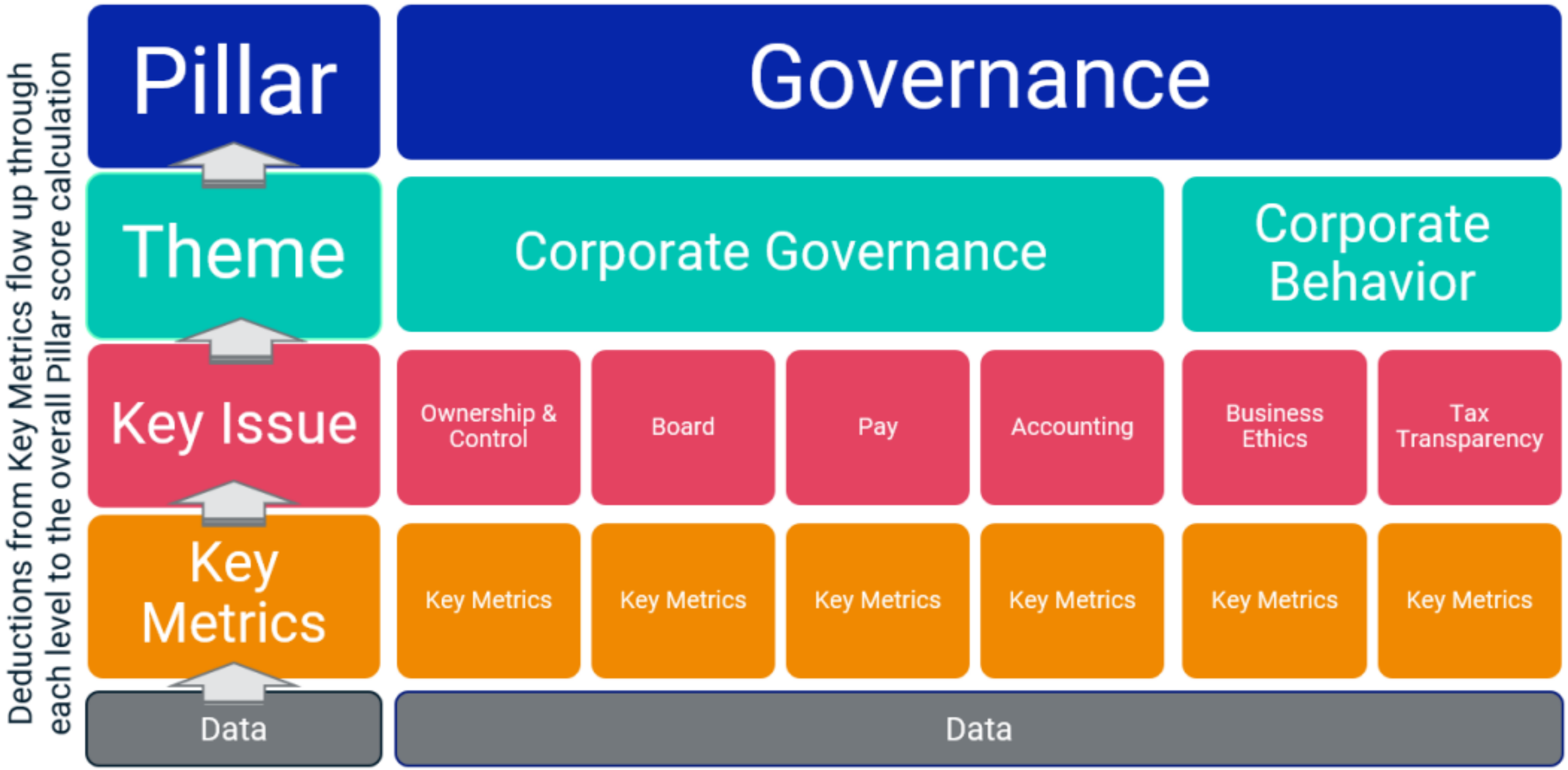
Source: https://www.msci.com/documents/1296102/21901542/ESG-Ratings-Methodology-Exec-Summary.pdf

MSCI ESG Key Issue Hierarchy

3 Pillars	10 Themes	35 ESG Key Issues	
Environment	**Climate Change**	Carbon Emissions Product Carbon Footprint	Financing Environmental Impact Climate Change Vulnerability
	Natural Capital	Water Stress Biodiversity & Land Use	Raw Material Sourcing
	Pollution & Waste	Toxic Emissions & Waste Packaging Material & Waste	Electronic Waste
	Environmental Opportunities	Opportunities in Clean Tech Opportunities in Green Building	Opportunities in Renewable Energy
Social	**Human Capital**	Labor Management Health & Safety	Human Capital Development Supply Chain Labor Standards
	Product Liability	Product Safety & Quality Chemical Safety Consumer Financial Protection	Privacy & Data Security Responsible Investment Health & Demographic Risk
	Stakeholder Opposition	Controversial Sourcing Community Relations	
	Social Opportunities	Access to Communications Access to Finance	Access to Health Care Opportunities in Nutrition & Health
Governance	**Corporate Governance**	Ownership & Control Board	Pay Accounting
	Corporate Behavior	Business Ethics Tax Transparency	

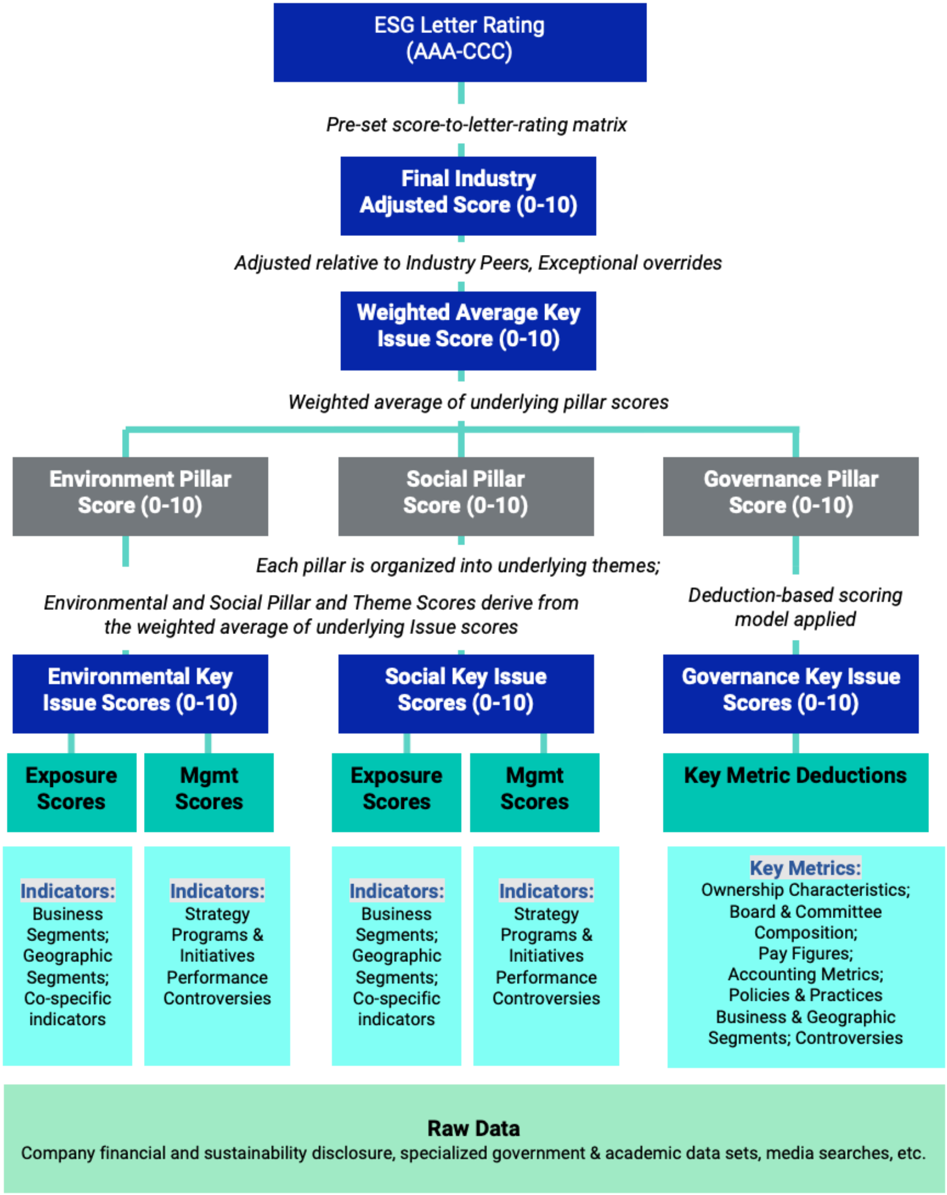
Source: https://www.msci.com/documents/1296102/21901542/ESG-Ratings-Methodology-Exec-Summary.pdf

MSCI Governance Model Structure



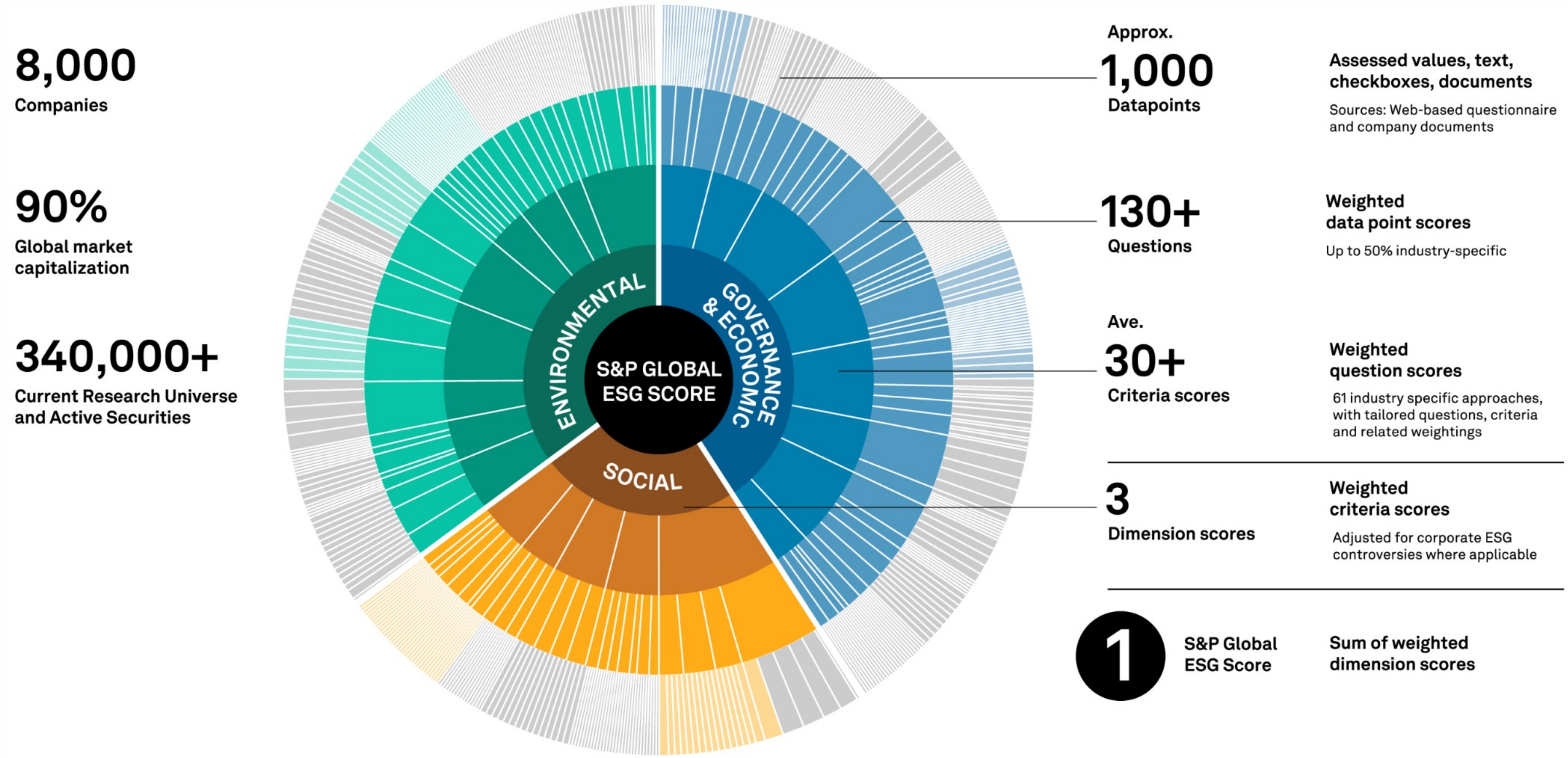
Source: https://www.msci.com/documents/1296102/21901542/ESG-Ratings-Methodology-Exec-Summary.pdf

MSCI Hierarchy of ESG Scores



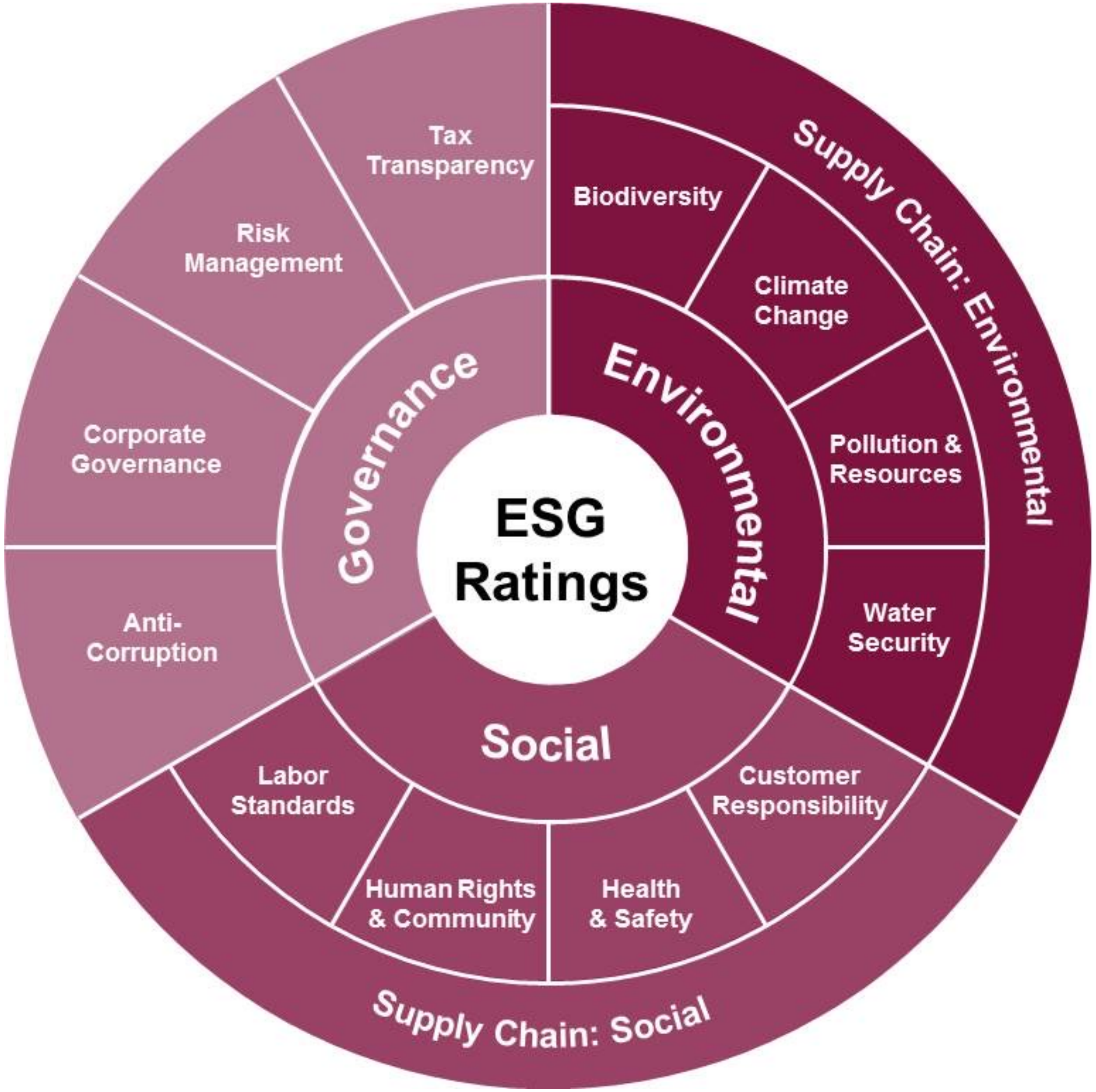
Source: https://www.msci.com/documents/1296102/21901542/ESG-Ratings-Methodology-Exec-Summary.pdf

DJSI S&P Global ESG Score



Source: DJSI, S&P Global Corporate Sustainability Assessment (CSA), https://www.spglobal.com/esg/solutions/data-intelligence-esg-scores

FTSE Russell ESG Ratings



Source: https://www.ftserussell.com/data/sustainability-and-esg-data/esg-ratings

SUSTAINALYTICS
a Morningstar company

Sustainalytics ESG Risk Ratings

Analyst-based approach

Sustainalytics' ESG Risk Ratings measure a company's exposure to industry-specific material ESG risks and how well a company is managing those risks.

Negligible	Low	Medium	High	Severe
0 - 10	10 - 20	20 - 30	30 - 40	40+

Source: https://www.sustainalytics.com/esg-data

TruValue Labs

FACTSET

Truvalue ESG Ranks

Machine-based approach

- **Truvalue Labs** applies **AI** to analyze over **100,000 sources** and uncover **ESG risks** and opportunities hidden in **unstructured text**.
- The ESG Ranks data service produces an overall company rank based on industry percentile leveraging the **26 ESG categories** defined by the **Sustainability Accounting Standards Board (SASB)**.
- The data feed covers 20,000+ companies with more than 13 years of history.

Laggard	Below Average	Average	Above Average	Leader

Source: :https://developer.truvaluelabs.com/data/esg-ranks

Analyst-driven vs. AI-driven ESG

Analyst-driven ESG research

Derives ratings in a structured data model

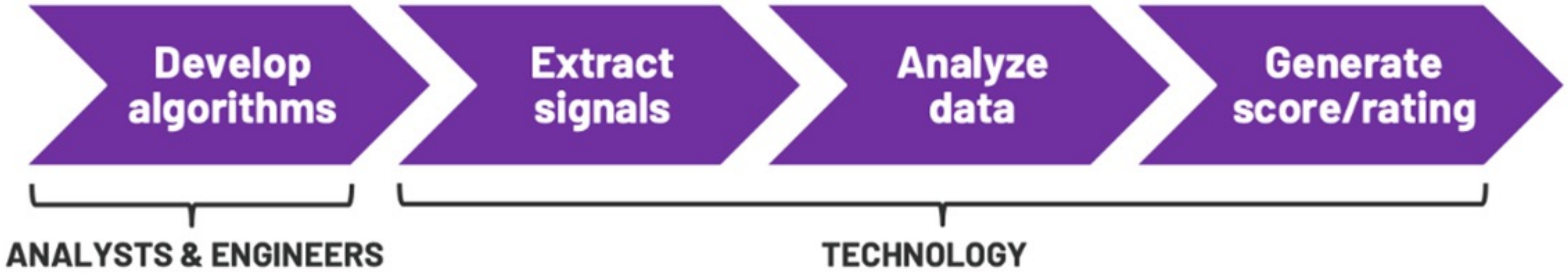
Sustainalytics

Analyst role at the end of the process allows subjectivity to color results

AI-driven ESG research

Derives signals from unstructured data

Truvalue Labs

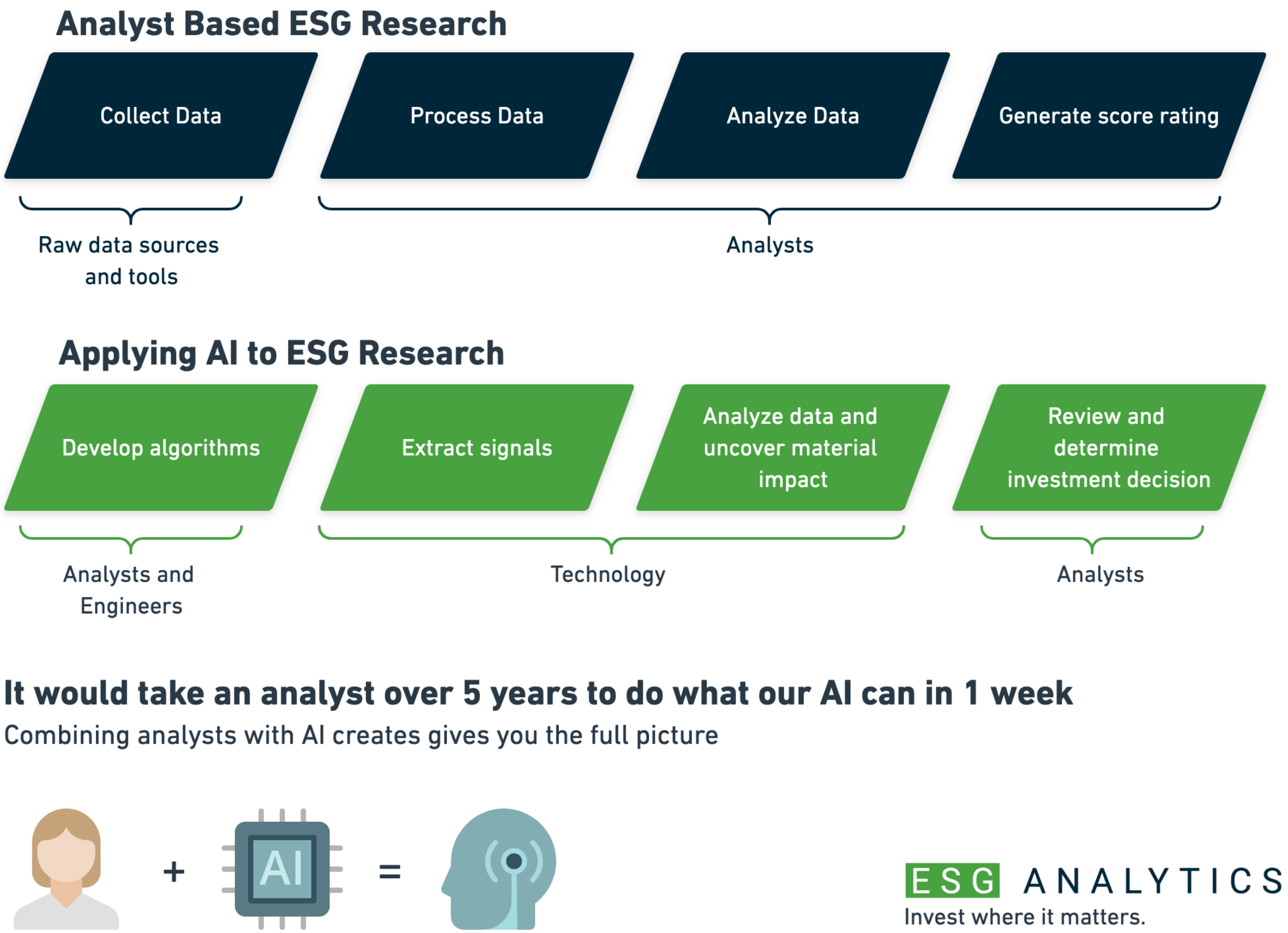


Analyst expertise at the beginning of the process produces consistent results

Source: Mark Tulay (2020), Man vs. machine: A tale of two sustainability ratings systems, GreenBiz, https://www.greenbiz.com/article/man-vs-machine-tale-two-sustainability-ratings-systems

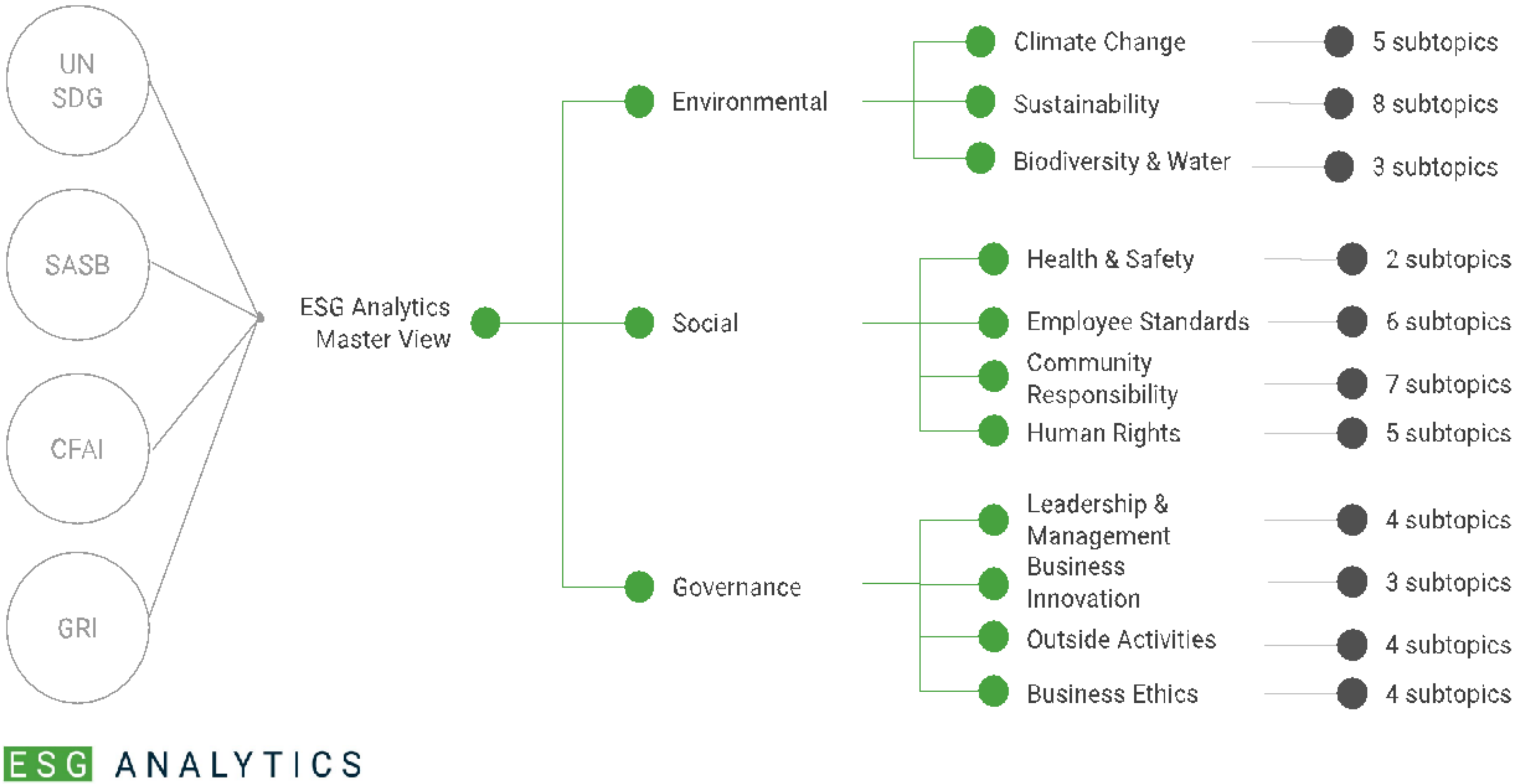
Analyst based ESG Research

AI based ESG Research



Source: https://www.esganalytics.io/insights/how-data-is-accelerating-esg

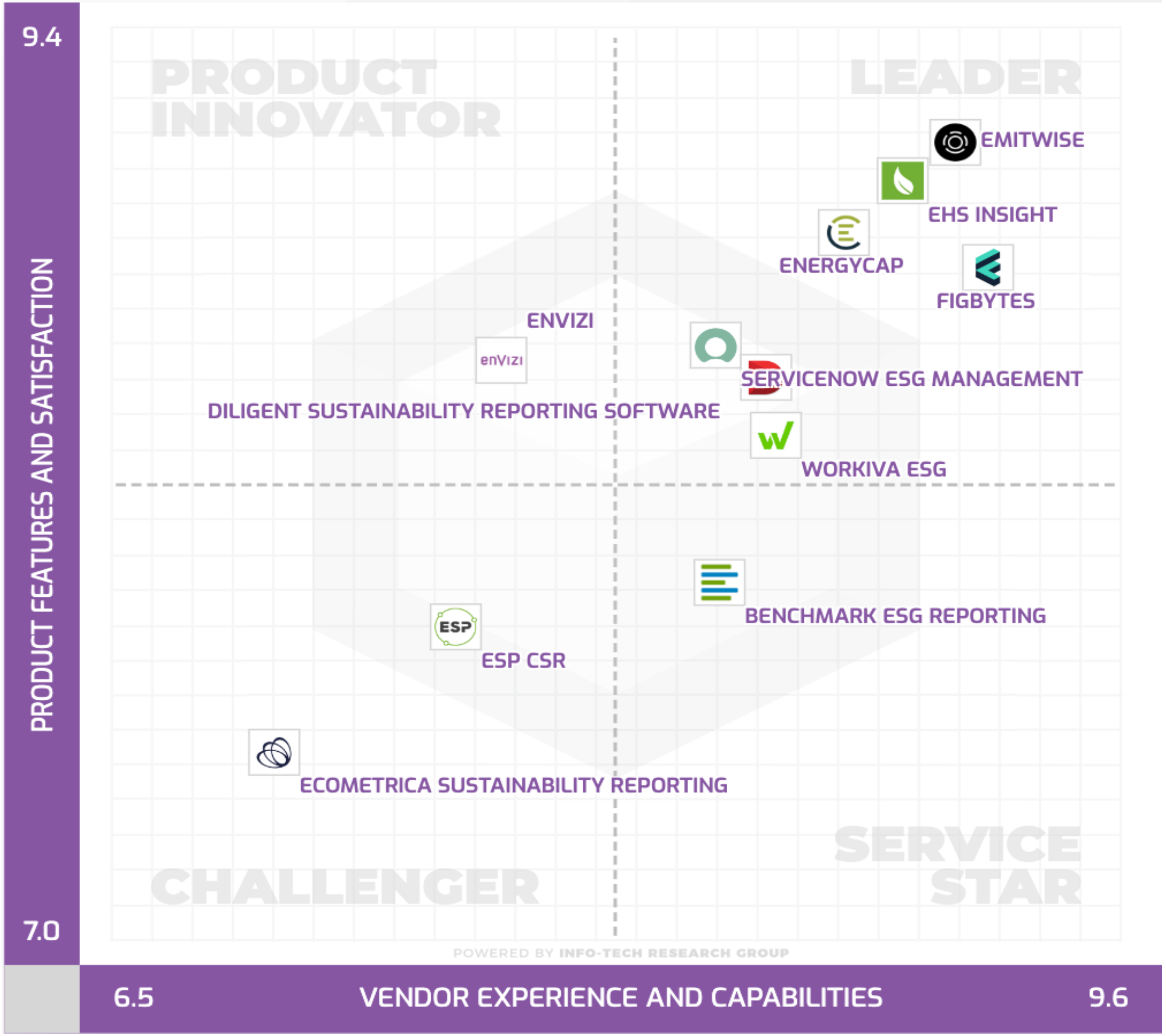
ESG Analytics: NLP Taxonomy



Source: https://www.esganalytics.io/insights/how-data-is-accelerating-esg

Top ESG Reporting Software

Environmental, Social and Governance (ESG) Reporting software or **Sustainability software** helps organizations **manage** their **operational data**, **evaluate** their **impact** on the **environment** and **provide reporting** to **perform audits**.



Source: https://www.softwarereviews.com/categories/environmental-social-and-governance-reporting

ESG Reporting Software: Emitwise

- Emitwise is the carbon management platform for companies with complex manufacturing supply chains to confidently understand, track and reduce their complete carbon footprint.
- Combining 100 years of carbon accounting experience and machine learning technology, we accelerate climate action by increasing the accuracy of scope 3 emissions.
- The platform empowers manufacturers and their supply chains to make carbon-led business decisions that lower risk, increase profitability and deliver ambitious climate action.

9.2	9.3	+99	94%
COMPOSITE SCORE	CX SCORE	EMOTIONAL FOOTPRINT	LIKELINESS TO RECOMMEND

Source: https://www.softwarereviews.com/categories/environmental-social-and-governance-reporting

ESG Reporting Software: Workiva ESG

- Workiva is a cloud native platform that simplifies the complexities of reporting and compliance.
- Workiva ESG is the end-to-end platform that allows you to integrate financial data, nonfinancial data, and XBRL.
- Workiva, the platform that streamlines your entire ESG process.
- Automate data collection, utilize frameworks, and directly connect to all your ESG reports. in meaningful glossy reports, accurate survey responses, and regulatory filings with integrated XBRL tagging.

8.4	8.7	+92	89%
COMPOSITE SCORE	CX SCORE	EMOTIONAL FOOTPRINT	LIKELINESS TO RECOMMEND

Source: https://www.softwarereviews.com/categories/environmental-social-and-governance-reporting

AI for Social Good (AI4SG)

Source: Nenad Tomašev, Julien Cornebise, Frank Hutter, Shakir Mohamed, Angela Picciariello, Bec Connelly, Danielle Belgrave et al. (2020) "AI for social good: unlocking the opportunity for positive impact." Nature Communications 11, no. 1: 1-6.

AI for Social Good (AI4SG)
AI for Sustainable Development
AI4SG 10 Guidelines

- **AI Technology (G1, G2, G3)**
- **Applications (G4, G5, G6, G7, G8)**
- **Data Handling (G9, G10)**

Source: Nenad Tomašev, Julien Cornebise, Frank Hutter, Shakir Mohamed, Angela Picciariello, Bec Connelly, Danielle Belgrave et al. (2020)
"AI for social good: unlocking the opportunity for positive impact." Nature Communications 11, no. 1: 1-6.

AI4SG 10 Guidelines
AI Technology (G1, G2, G3)

- **G1: Expectations of what is possible with AI need to be well-grounded.**
- **G2: There is value in simple solutions.**
- **G3: Applications of AI need to be inclusive and accessible, and reviewed at every stage for ethics and human rights compliance.**

Source: Nenad Tomašev, Julien Cornebise, Frank Hutter, Shakir Mohamed, Angela Picciariello, Bec Connelly, Danielle Belgrave et al. (2020) "AI for social good: unlocking the opportunity for positive impact." Nature Communications 11, no. 1: 1-6.

AI4SG 10 Guidelines Applications (G4, G5, G6, G7, G8)

- **G4: Goals and use cases should be clear and well-defined.**
- **G5: Deep, long-term partnerships are required to solve large problems successfully.**
- **G6: Planning needs to align incentives, and factor in the limitations of both communities.**
- **G7: Establishing and maintaining trust is key to overcoming organisational barriers.**
- **G8: Options for reducing the development cost of AI solutions should be explored.**

Source: Nenad Tomašev, Julien Cornebise, Frank Hutter, Shakir Mohamed, Angela Picciariello, Bec Connelly, Danielle Belgrave et al. (2020) "AI for social good: unlocking the opportunity for positive impact." Nature Communications 11, no. 1: 1-6.

AI4SG 10 Guidelines
Data Handling (G9, G10)

- **G9: Improving data readiness is key.**
- **G10: Data must be processed securely, with utmost respect for human rights and privacy.**

Source: Nenad Tomašev, Julien Cornebise, Frank Hutter, Shakir Mohamed, Angela Picciariello, Bec Connelly, Danielle Belgrave et al. (2020) "AI for social good: unlocking the opportunity for positive impact." Nature Communications 11, no. 1: 1-6.

AI for Social Good (AI4SG)

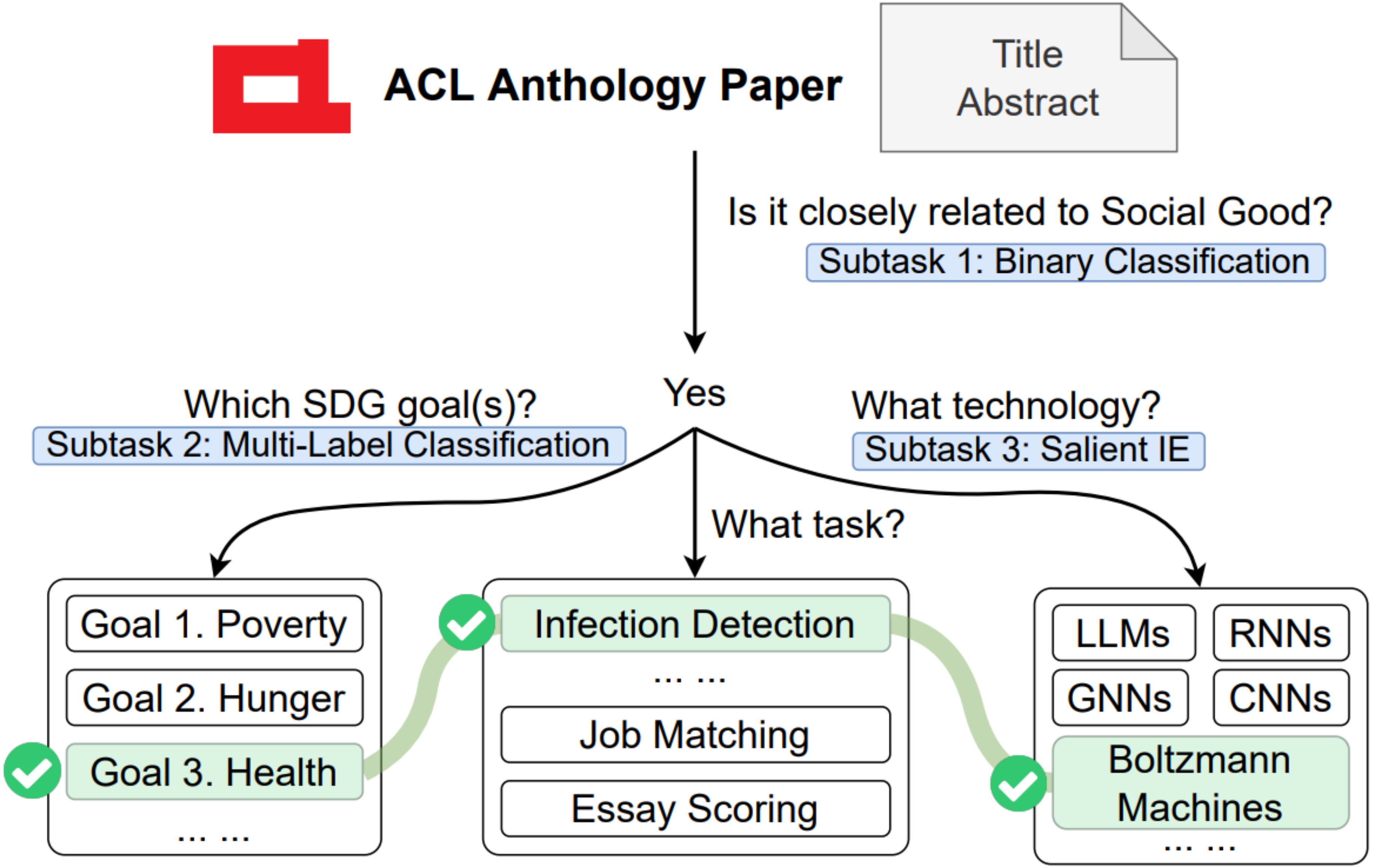
Domains and Techniques

Technique	Agriculture	Education	Environmental sustainability	Healthcare	Combating information manipulation	Public safety	Social care and urban planning	Transportation	Total
Cognitive modeling	0	0	0	0	0	1	0	0	1
Constraint satisfaction and optimization	2	5	31	48	20	26	9	59	173
Cognitive systems	1	2	2	7	2	3	1	5	20
Computer vision	3	8	12	20	6	12	7	19	79
Game playing and interactive entertainment	0	1	0	1	0	0	0	0	2
Game theory and economic paradigms	3	5	30	6	11	31	1	16	78
Human-AI collaboration	1	8	11	23	9	6	6	17	69
Human computation and crowd sourcing	1	5	6	20	45	12	11	15	98
Heuristic search and optimization	1	3	11	14	8	8	6	26	69
Knowledge representation and reasoning	0	0	0	5	3	2	0	1	11
Multiagent systems	2	7	47	19	16	22	8	31	122
Machine learning	12	27	65	174	53	65	36	92	460
Natural language processing	4	12	6	18	10	10	5	3	58
Planning, routing, and scheduling	9	4	48	43	14	28	31	84	210
Robotics	3	4	12	10	4	5	4	10	47
Reasoning under uncertainty	4	3	30	23	8	6	6	13	78
Total	40	78	225	344	155	177	90	253	1176

Domain

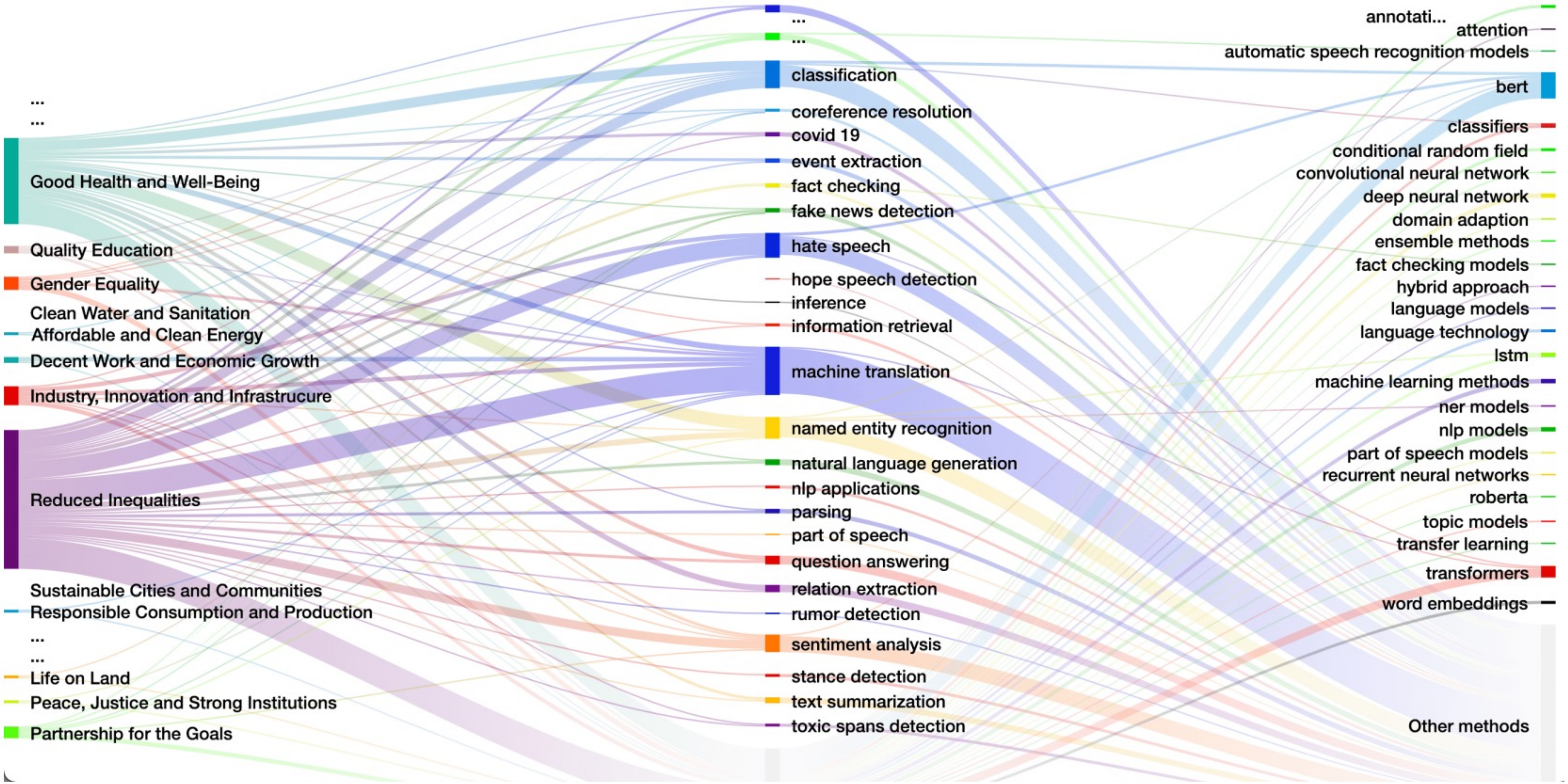
Source: Zheyuan Shi, Ryan, Claire Wang, and Fei Fang (2020). "Artificial intelligence for social good: A survey." arXiv preprint arXiv:2001.01818.

NLP for Social Good (NLP4SG)



Source: Fernando Gonzalez, Zhijing Jin, Jad Beydoun, Bernhard Schölkopf, Tom Hope, Rada Mihalcea, and Mrinmaya Sachan (2022). "How Is NLP Addressing the 17 UN Sustainability Goals? A Challenge Set of Social Good Paper Classification and Information Extraction."

NLP for Social Good (NLP4SG) Visualization



Source: Fernando Gonzalez, Zhijing Jin, Jad Beydoun, Bernhard Schölkopf, Tom Hope, Rada Mihalcea, and Mrinmaya Sachan (2022). "How Is NLP Addressing the 17 UN Sustainability Goals? A Challenge Set of Social Good Paper Classification and Information Extraction."

Innovation

Innovation:

a <u>new</u> 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

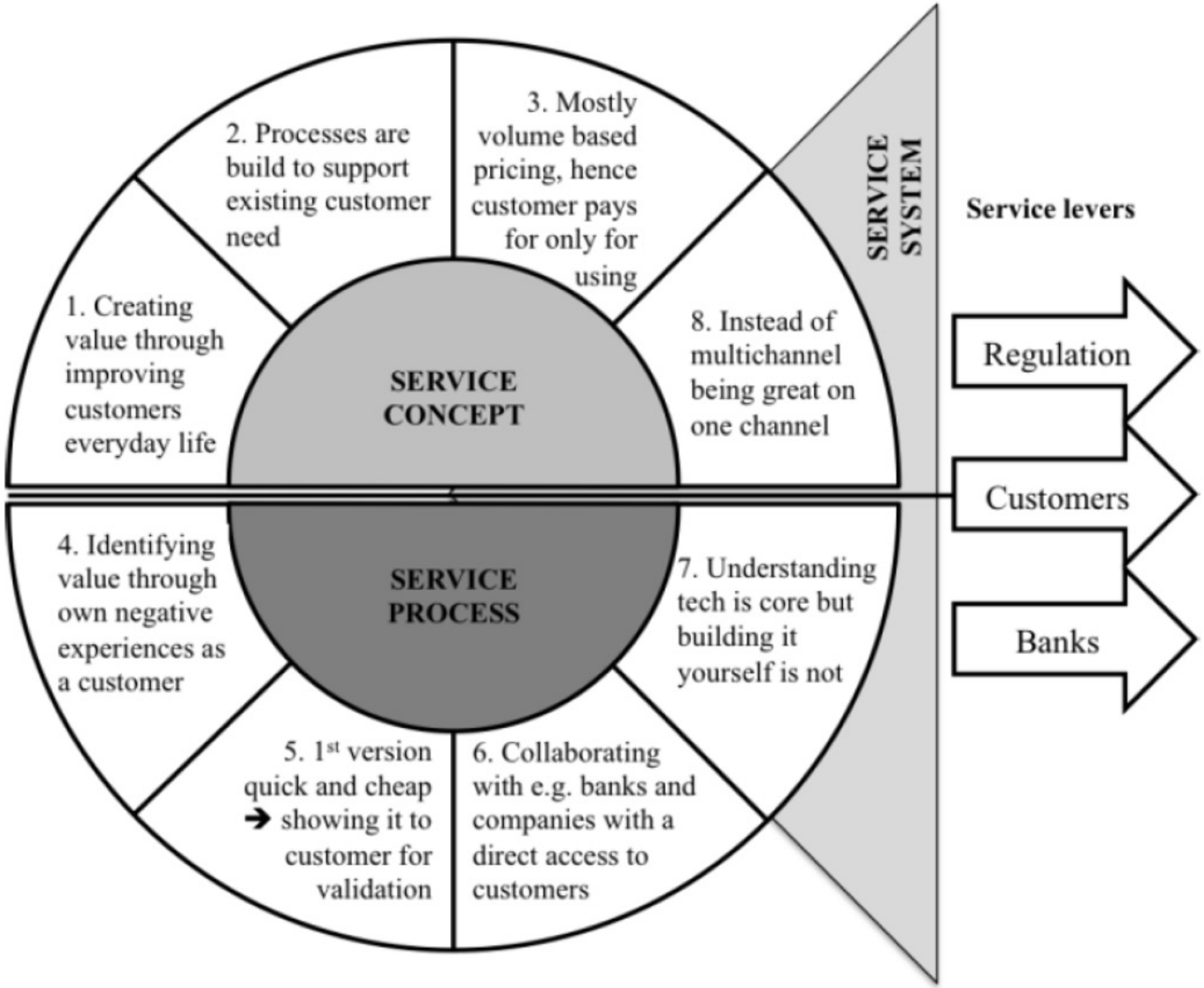
new Idea.

Creativity is

an old belief

you leave behind

FinTechs as Service Innovators: Analysing Components of Innovation



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

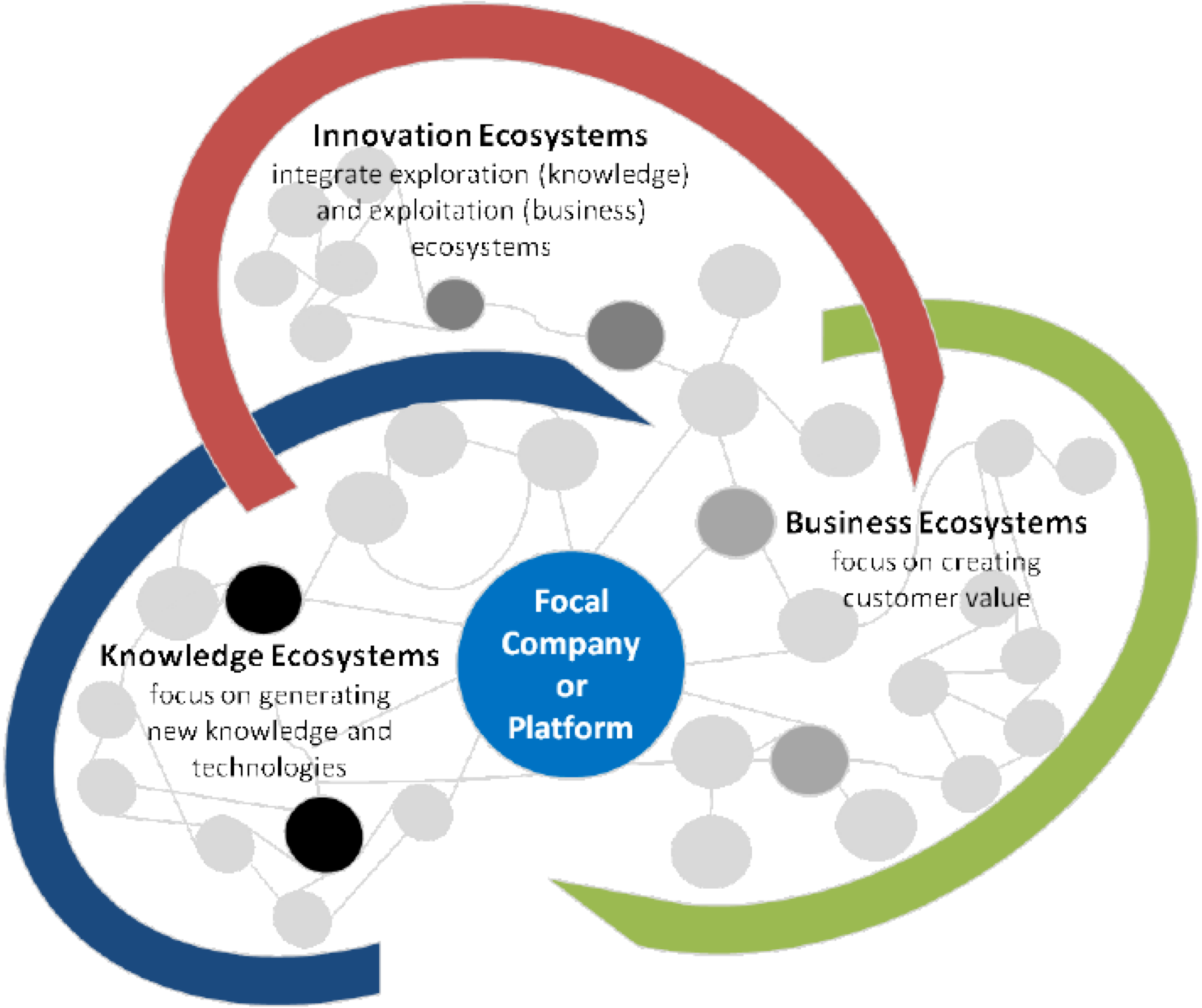
	Stage of process	Level of study	Type of innovation
Economists	Generation Idea generation Project definition	Industry	Product and process Only technical Only radical
Technologists			
Contextual technologists	Generation Commercialization and marketing Diffusion	Innovation (in the industry context)	Product 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



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)

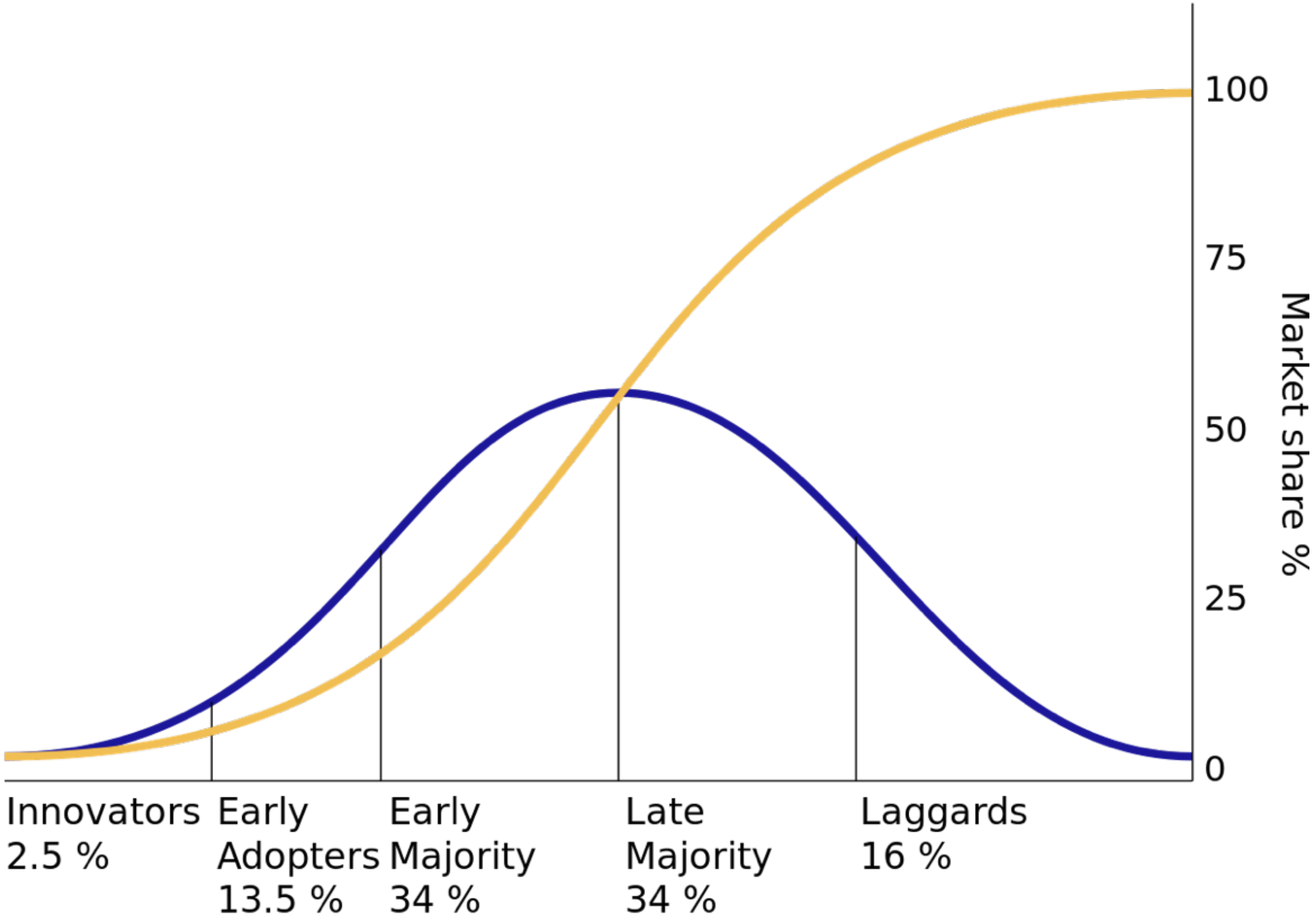
Source: Everett M. Rogers (2003), “Diffusion of Innovations”, Free Press, 5th Edition

Innovation
(Diffusion of Innovation)

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

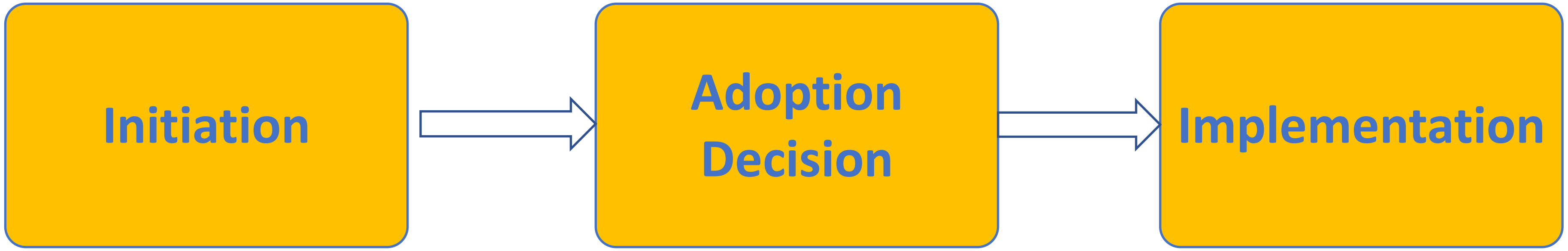
Source: Everett M. Rogers (2003), “Diffusion of Innovations”, Free Press, 5th Edition

Diffusion of Innovation



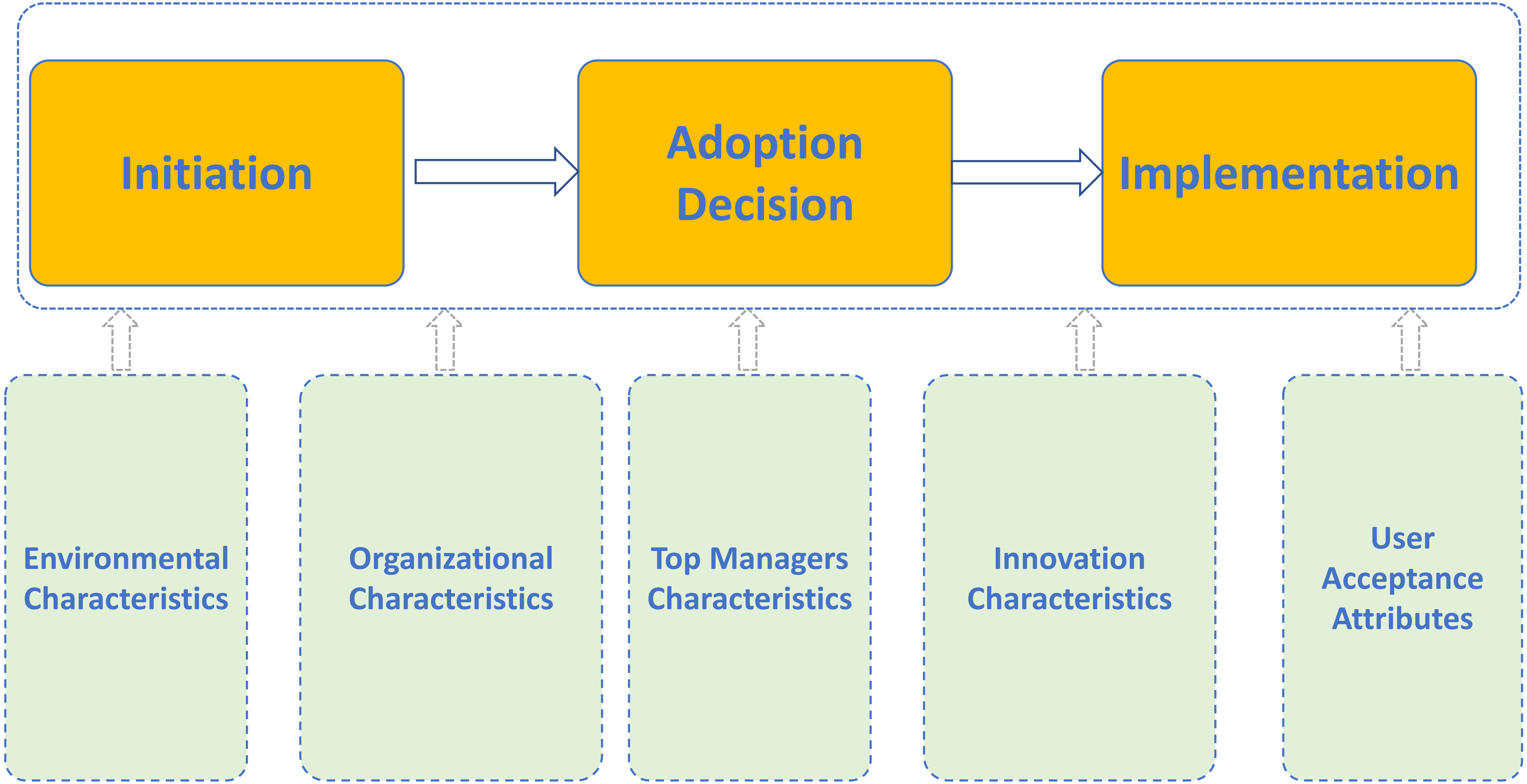
Source: https://en.wikipedia.org/wiki/Diffusion_of_innovations

Innovation Adoption Process



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

Innovation Adoption Process



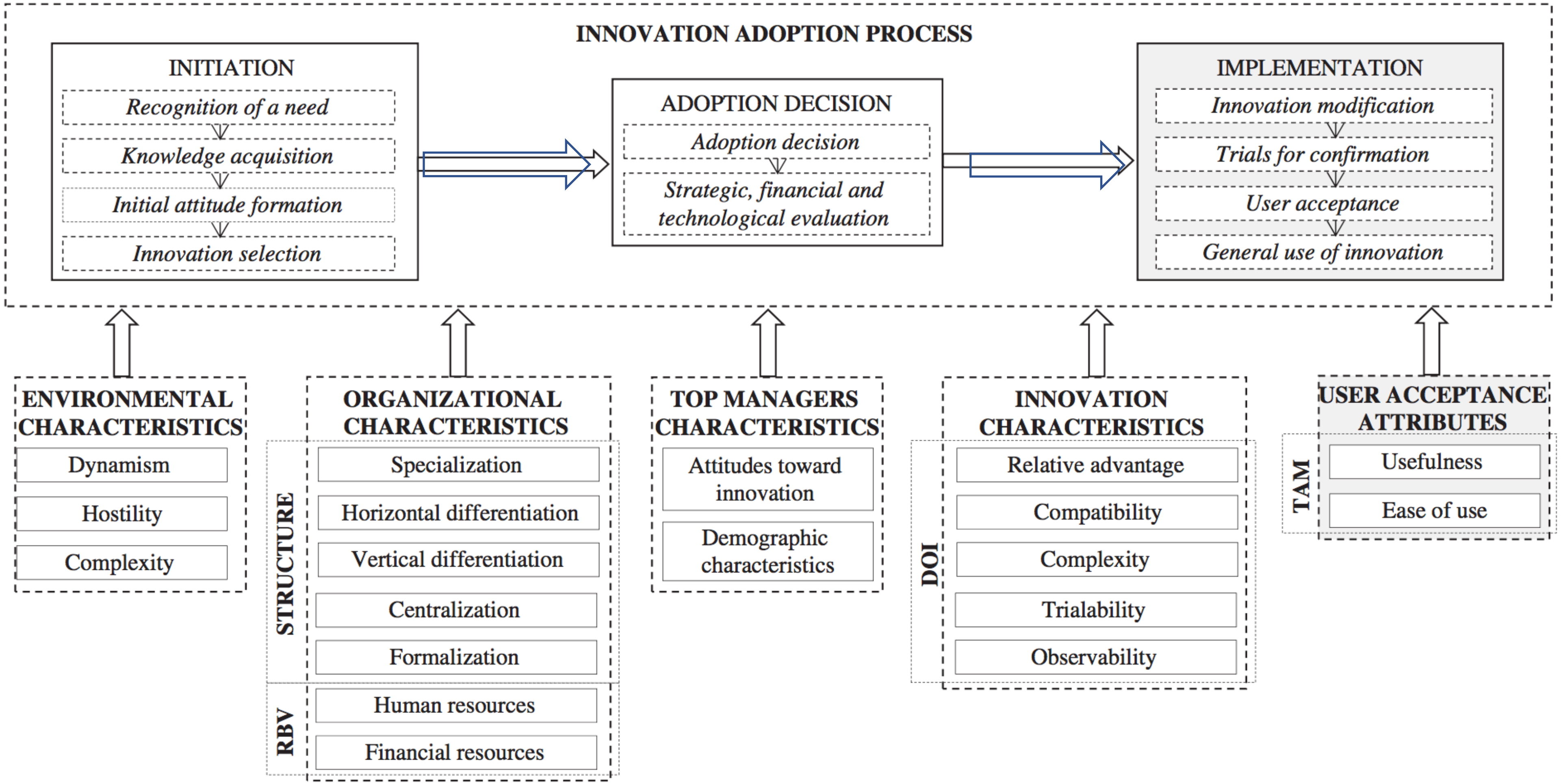
RBV=
Resource-Based View

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



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

		Initiation					*Adoption decision*					*Implementation*				
Factors		*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

Robo Advisors:

- Profile
- Advice
- Re-Balance
- Indexing

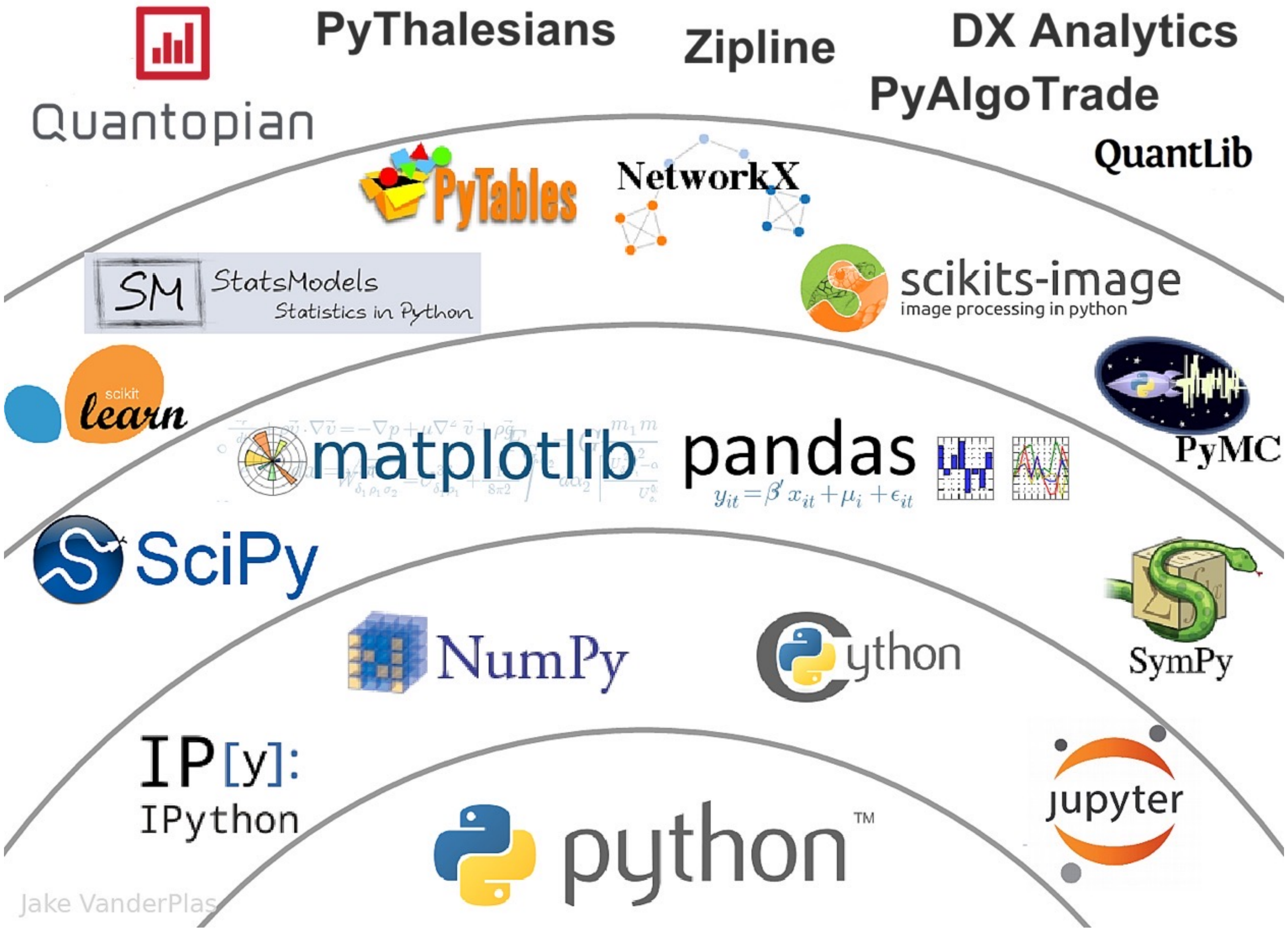
Source: Paolo Sironi (2016), “FinTech Innovation: From Robo-Advisors to Goal Based Investing and Gamification”, Wiley.

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

The Quant Finance PyData Stack



Source: http://nbviewer.jupyter.org/format/slides/github/quantopian/pyfolio/blob/master/pyfolio/examples/overview_slides.ipynb#/5

Python in Google Colab (Python101)

python101.ipynb

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- Financial Functions (ffn): https://pmorissette.github.io/ffn/
- backtesting.py: https://kernc.github.io/backtesting.py/

15s

```
!pip install ffn
import ffn
import plotly.express as px
%pylab inline
#BTC-USD Bitcoin USD
df = ffn.get('btc-usd', start='2016-01-01', end='2021-12-31')
print('df')
print(df.head())
print(df.tail())
print(df.describe())
df.plot(figsize=(14,10))

returns = df.to_returns().dropna()
print('returns')
print(returns.head())
print(returns.tail())
print(returns.describe())
#ax = df.plot(figsize=(12,9))

perf = df.calc_stats()
perf.plot(figsize=(14, 10))
```

https://tinyurl.com/aintpupython101

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