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BIG DATA ANALYTICS: DIRECTION AND IMPACT ON FINANCIAL TECHNOLOGY

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ABSTRACT

Purpose- Digital infrastructure and technology advancements are steering the innovations in financial sector globally. The technology and data driven aspect has fueled the Fintech sector, evolving at the tangent of mighty finance sector and revolutionary technology domain, especially the digital technologies. The purpose of this paper is to show that most FinTech innovations, are significantly driven by big data analytics and its efficient implementation.

Methodology- The use of latest ICT technologies lightens up the finance operations and services to exponential levels. Big data analytics is new and requires comprehensive studies as a research field specially in the finance domain. The intent here is to study an adoption model specially IT diffusion mode to Big data analytics that could detect key success predictors. The study tests the model for adoption of big data as novel technology and the related issues. The paper also presents a review of academic journals, literature, to study the diffusion and adoption of big data in to the finance domain.

Findings - The research reflects a significant interest and utility about Big data analytics value that epitomizes the rise of Fintech phenomenon. Big data analytics may provide some competencies to the organizations that may consider its several dimensions along with its framework in the pre-adoption phase or adoption phase or implementation or diffusion phase. The research also attempts to describe the several dimensions of Big data analytics as a new technology. This shall be of good interest to the researchers, professionals, academicians and policy-makers.

Conclusion- The paper first defines big data to consolidate the different discourse and literature on big data. We also reflect the point that predictive-analytics (with structured data) overshadows other forms: descriptive and prescriptive analytics (with unstructured data) which constitutes more than 90% of big data. We also reflected on analytics techniques for unstructured data: audio, video, and social media data, as well as predictive analytics. In the analysis and testing part we also performed the testing of the IT diffusion model which concludes that there are significant relationships among IT-planning, IT-implementation and IT-diffusion.

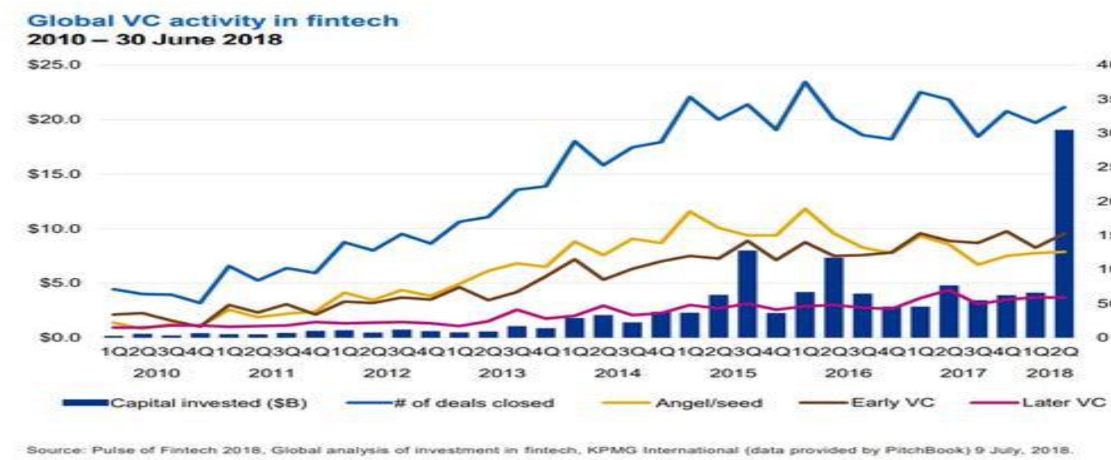
Keywords: Fintech, big data analytics, IT diffusion, digital payment
JEL Codes: M10, M15, O32, O33.

1. INTRODUCTION

Data analytics, especially big data analytics is claiming its due place in the industry and academia equally. The domains of business and management are embracing all phases of data analytics starting from descriptive data analytics towards prescriptive data analytics through predictive data analytics. Finance, retail, health sector, supply chain and almost every sector is practicing this novel technique in the areas of wealth management, credit management, market basket analysis, apriori algorithms, health prediction and prescription, etc. The advancements in digital technologies especially the new age sensors and other input devices are capturing more and more data ranging in zeta bytes throughout and unending. The result is that the size of data is becoming enormous, mammoth, highly voluminous in the form of 'Big Data', which in turn is being transformed in to business value through business intelligence and big data analytics. The value hidden in the patterns of big data is being unlocked through modeling, visualizations, knowledge discovery, adaptive algorithms and some other techniques.

Fintech is a phenomenon in the service sector which utilizes digital technology to boost the efficiency in the new age financial system with both set ups – legacy as well as startups. This buzz word is a combination of "finance" and "technology", which collectively implies the transformations achieved through the convergence of financial services and digital technology. Major Indian examples are Paytm, freecharge, phonepe, payzapp. These companies offer new business models that promise more flexibility, security, efficiency, and opportunities than established financial services (Lee 2015a). The innovator can be a new age start-up (payU), a well-established technology company (payzapp- HDFC Bank), or a well-established service provider (like jiomoney).

Figure 1: Pulse of Fintech 2018, Source: KPMG International



The literature shows the significant work in the domains of big data, financial technology or fintech and the testing of IT diffusion model separately. No paper till now has focused on the impact of big data analytics on the fintech sector and tested the diffusion of big data as technology in the fintech sector. This paper contributes the testing of IT diffusion theory of big data analytics as technology on the fintech sector. Further this research also put light on the different dimensions of big data as emerging technology along with its centricity in the fintech sector. This paper also put together the different concepts and evolution on the fintech sector. The integration of these concepts and an empirical testing will help the scholars to understand the potential of big data in the fintech sector and will help further in the future research. Studying the impact of Big Data Analytics in the financial sector gives a rise to the Fintech phenomenon**.** The research questions for the study;

RQ1. How Fintech companies are driven by big data analytics and its efficient implementation?

RQ2. What are the key success predictors through adoption model of Big Data Analytics?

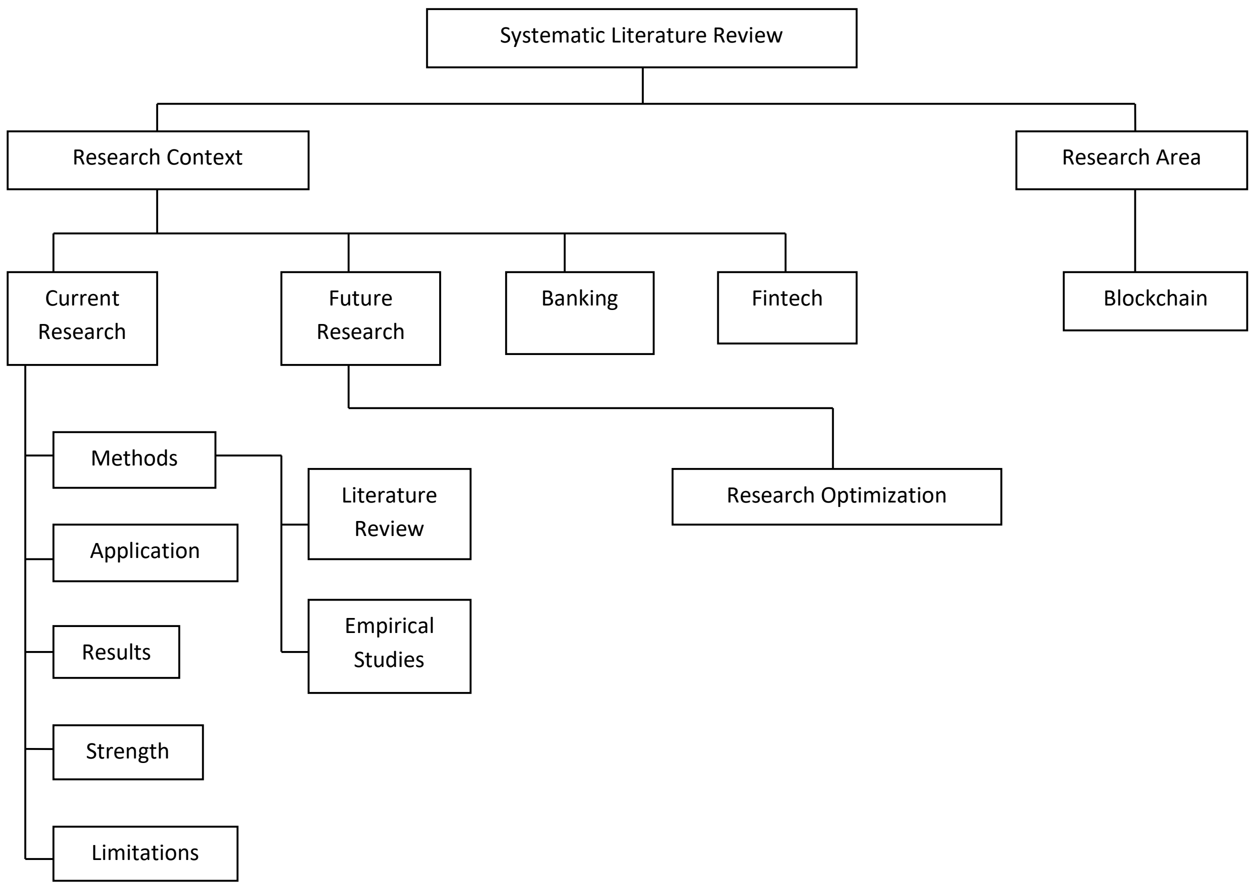
RQ3. What are the different dimensions of Big Data Analytics as a technology?

Flow of paper: This research paper starts with the introduction to Fintech, Data Analytics and Big Data along with examples and the activity in the Fintech sector, followed by a comprehensive review of literature across the major databases. The criteria for inclusion or exclusion is defined specifically in the review. The third part of the paper explains the research methodology followed to conduct the overall research including hypothesis, questionnaire design, research design, data analysis, otology, taxonomy, four eras of fintech and important concepts. The fourth part of the paper focus on Big Data Analytics for Fintech and it also focus on the Technology Diffusion Theory and its use for Fintech Research in this paper. The fifth and penultimate part shows the results of this research through various tables, a figure and hypothesis testing results. In the last this paper is concluded with major takeaways and its importance for future researchers and scholars.

2. LITERATURE REVIEW

The methodology used for the selection and preparation of this paper is presented in Figure 1. The SLR blueprint is broadly classified as i. Research Context, and ii. Research Area. This research covers first, the contemporary research inter-linking information in terms of methodology, applications, result of the study, strengths, and limitations, if any using published research articles. Two type of research were examined, namely, review of the literature and empirical study based publications. The selected databases are EBSCO, Emerald, Elsevier, ProQuest, Scopus and Google Scholar digital databases with linear and cross searches. Secondly, it covers the future research and directions highlighting the direction of the research. The research area of this study is targeted to banking and fintech industry.

Figure 2: Systematic Literature Review Map



2.1. Criteria for Inclusion

The following criteria for inclusion (CfI) is utilized to select the research papers for review:

CfI 1: The keywords used are: "big data", "big data analytics", "technology diffusion", "financial technology", "fintech". The operators used as syntax are OR and AND. The AND operator states that both keywords must be there in the search-queries and operator OR means that at least one of the keywords must be there in the query.

CfI 2: Publications before March 31, 2020

CfI 3: Publications in English

CfI 4: Document type: journal articles

CfI 5: Studies based on abstract and

CfI 6: full-text-based studies

2.2. Criteria of Exclusion

The criteria of exclusion (CoE) that is used to filter out the studies are:

CoE 1: Duplicate studies with matching title

CoE 2: Matchng Digital Object Identifier, doi.

Digital Database- The digital databases utilised to collect the data for the review of papers are;

i) IEEE ii) Emerald iii) Elsevier iv) ProQuest v) Springer vi) Google Scholar

Review Protocol Development- Google Scholar was considered for extracting papers from these digital databases because;

i) there is an extensive amount of studies available in context with our topic that are indexed,

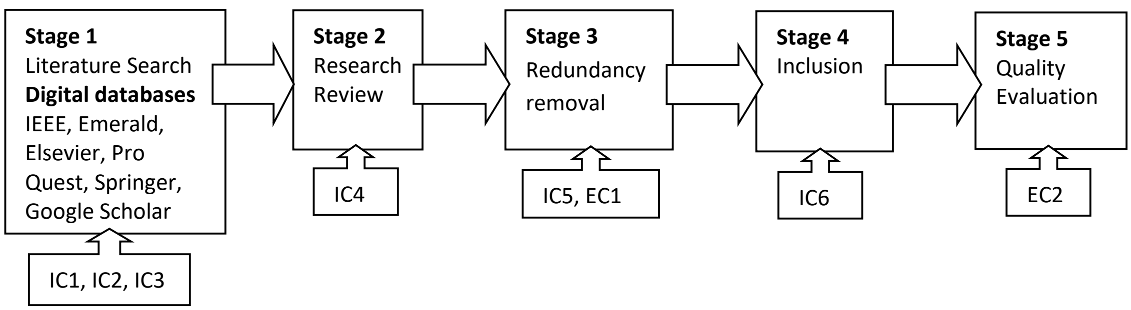
ii) it is the leading digital literature database which includes peer reviewed papers,

iii) it has extensive scientific and inter disciplinary information.

EBSCO, Emerald, Elsevier, ProQuest and Scopus were also reviewed for the papers.

Review Protocol Evaluation- In order to execute the inclusion criteria, exclusion criteria, and the selection of research papers, it is important to examine and evaluate the quality of the papers. In fact, the aim of this assessment is to make sure that the results of this study comes as suitable and impartial as possible. The different stages for data selection are shown in Figure 2 in a sequential manner. Each of the stage shown in the figure is executed with the accompanying IC, inclusion criteria and EC.

Figure 3: Data Selection Stages



3. RESEARCH METHODOLOGY

A descriptive research approach with Positivism is followed in this paper to study the relationship between the trust factor and usage attitude and the research study is having a body of knowledge and research hypotheses. To summarize and generalize the hypotheses testing, a quantitative study is carried out for this study that is derived from the existing theory of IT diffusion. Primary data is collected through the self-administered questionnaires.

RQ1.
How Fintech companies are driven by big data analytics and its efficient implementation?
Literature review

RQ2.
What are the key success predictors through adoption model of Big Data Analytics?
Literature review

RQ3.
What are the different dimensions of Big Data Analytics as a technology?
Three Dimensional IT Adoption Model Testing through empirical data

Hypothesis
The following set of hypotheses, as derived from the literature and our own research questions, were derived:
H1: Significant factors are there in IT planning.
H2: Significant factors are there in IT implementation.
H3: Significant factors are there in IT diffusion.
H4: Significant relationships exist among IT planning, implementation, and diffusion.

Questionnaire Design- The questionnaire was designed in two sections, A and B for data collection. The demographic variables are gender, age, academic qualification level were included in part A and section B included the variables are used to measure the tested constructs. All of the required/tested constructs were measured by the most efficient scale: Likert Scale on five points (1-strongly disagree to 5- strongly agree).

Research Design

Sample Population: Engineers and Managers working at fintech companies in Gurugram, Haryana.

Target: PayU, LoanSimple, INDmoney, Freecharge, Home Credit, Hora.AI, PaisaDukan

Sample Size: 100

Sample unit: Individual Engineers and Managers

Area of study: Gurugram, Haryana

Respondents: Employees of fintech companies located in the millennium city Gurugram.

Sampling Technique: Non-probability sampling, Judgmental sampling technique.

Reliability: To ensure that the questionnaire is error free, a pilot study was conducted.

Method: Self-administered survey was done after the feedback of the pilot study/test. Medium: emailed surveys, monkeysurvey.com and google forms were used

Data Analysis- To perform the statistical analysis SPSS - 22.0 was used, including varimax rotation and hypothesis testing. Other analysis includes; inferential analysis (multiple regression analysis), Descriptive analysis, scale measurement (reliability and validity tests).

Reliability Test: The degree in which the scale measurements are free from errors and yields consistent result from the study (Bajpai, 2011). Cronbach's alpha was used in this research to evaluate the reliability of the scale measurement.

Validity Test: Construct validity was adopted in this research as validity measurement and exploratory factor analysis (EFA) was used to measure the construct validity (Cavana et al., 2001). The output of the factor analysis (FA) was indicated in the results as proper. Kaiser-Meyer-Olkin (KMO) = 0.66 (between 0.5 and 1.0) and Bartlett test of sphericity was significant (p=0.000; df =77; approx. Chi-Square=1716.216) for all the correlations.

The VARIMAX in orthogonal rotation was done in the factor analysis (FA), based on the principal components analysis.

Eigen-values for all the tested constructs were greater than 1.0.

Varimax-rotation is done to simplify the expression or model of a particular sub-space in terms of some major items in the mathematical form (squared correlations between variables and factors). Varimax maximizes the sum of the variances of the squared factor loadings. The actual coordinate system is kept un-changed and it is generally the orthogonal basis that is being rotated to align with those coordinates. The sub-space found with the principal component analysis (PCA) or factor analysis (FA) is expressed as a dense basis with many non-zero weights which can make it hard to interpret and understand. Preserving of the orthogonality requires that the rotation that leaves the sub-space invariant. This is achieved if,

(i) any given variable in the study has a higher factor loading on a single factor but a near-zero factor loadings on the other factors in the study and if

(ii) any given factor in the study is constituted or described by only a few variables with very high factor loadings on this factor while the other variables in the study have a near-zero factor loading.

If both of these conditions are true, then the factor loading matrix is assumed to have "simple structure," and the technique of varimax-rotation brings the factor loading matrix closer simple structure (as allowed by data). In context of individual loading measured on the variables under study, varimax provides and seeks a foundation that can represent each individual variable most economically, i.e. each individual can be sufficiently described by a linear combination of only a few basic functions. Varimax criterion can be expressed ss:

$$R_{\mathrm{VARIMAX}} = \arg\max_{R} \left(\frac{1}{p} \sum_{j=1}^{k} \sum_{i=1}^{p} (\Lambda R)_{ij}^4 - \sum_{j=1}^{k} \left(\frac{1}{p} \sum_{i=1}^{p} (\Lambda R)_{ij}^2 \right)^2 \right).$$

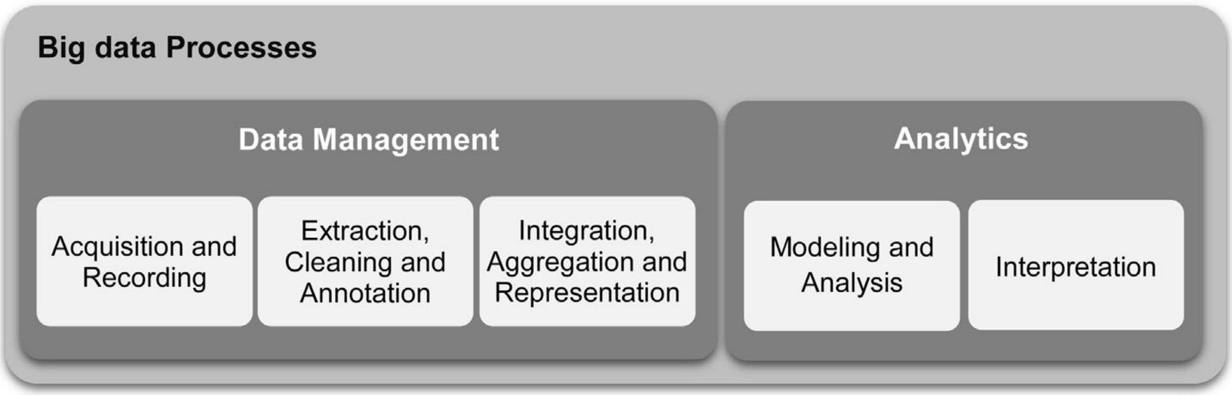
Source: Suggested by Henry Felix Kaiser in 1958

Big Data- Big data can be structured as well as unstructured, most of the data captured now is the unstructured one including audio, video, images and the unstructured text, which is beyond the structured capabilities of the conventional databases and software solutions. Huge amount of real time or stream data is being captured via sensors, CCTV cameras and other devices, which requires huge computational resources and capabilities in terms of storage and processing. Several new age software like Tableau and Microsoft tools are now capable of generating live business value and intelligence from the live data itself.

Big Data Analytics- Big data is valueless in isolation. Its potential business value is unlocked only when it is tested and processed with analytics for decision-making. To initiate an evidence or data based decision making, business organizations require efficient and intelligent processes to transform higher volumes of fast-pace and diversified data into meaningful and contextual business insights. The process of extracting and discovering insights from within big data can be divided into five different stages (Labrinidis

&Jagadish, 2012), shown in Fig. 3. These five stages can be clubbed into two main sub processes: big data-management and big data-analytics. Data-management includes the processes and technologies to capture, acquire and economically store data and to prepare and efficiently retrieve it for further analysis. Big data-analytics includes the techniques used to analyze and acquire intelligence and business value from big data. Therefore, big data analytics can be understood as a sub-process in the overall process of 'insight extraction' from big data – live or historical.

Figure 4: Processes for Extracting Insights from Big Data (A. Gandomi, M. Haider)



Finance and Technology – Fintech- This study argues that the FinTech should be understood in a broader context in at least two ways than as currently defined. The embrace of this broader conceptualization could be a sufficient condition to the proposition that big data analytics provides the central insight into FinTech. First, advancements in the domains information, communications and computer technologies (ICT) underlie most innovation in financial markets, starting centuries ago and until now. Second, financial innovation based on technological advances is hardly new, infact, it has been driving financial market development for much of history.

FinTech innovation has increased at high speed over the past three decades with the advent of financial engineering, a mathematically-based sub-discipline that largely focuses on arbitrage, derivatives and innovations in financial products, instrumentation and strategies. Today, FinTech assumes many forms with impact in financial sectors well beyond the scope of financial engineering. A FinTech taxonomy is advanced that should enable prompt reaction – a regulatory paradigm for remediation of FinTech malfunctions. This is a readiness paradigm enabling financial regulators and private party victims to intercede quickly when FinTech fails. A concise history of select FinTech watersheds is reviewed to illustrate both successful and failed FinTech regulatory approaches, and the role of digitizing huge historical databases to become FinTech big data.

Anticipatory FinTech regulation should be more broadly understood to target all major sectors of the financial industry as traditionally articulated, including,

(1) investment banking; (2) startup finance; (3) securities, derivatives and commodities;

(4) brokerage, dealers and financial intermediaries; (5) investment advice;

(6) corporate disclosure, investor relations and corporate democracy;

(7) new forms of money and currency transactions; and

(8) the monitoring and enforcement of money flows particularly Anti-Money Laundering controls (AML).

Many FinTechs appeal to the cyber-libertarian goal to achieve successful separation from societal control irrespective of the physical location of individuals or organizations. Stealth initial deployment, a chronic attribute of many FinTech, is examined as FinTech operations migrate to rogue havens making FinTech stubbornly resistant to revealing forensic quality evidence. Consider that many FinTechs employ the conventional supply chain elements of communicating, standardized documentary instrumentation, trading platforms and the sock exchange markets. FinTechs generally challenge the (value added) role of intermediaries.

Anticipatory FinTech Regulation is developed here as a big data approach to FinTech that balances three key FinTech influences;

(1) incentivizing FinTech innovation,

(2) enhancing market failure forensics and

(3) developing public policy resolutions to a broad array of FinTech challenges.

FinTech presents THE grand challenges in financial regulation and financial security today. Here we argue, big data analysis provides a balanced solution.

In case of crypto-currency, Bitcoin, the innovation and application has not achieved the expected wider adoption in the financial markets globally, at present. The hindrance obstructing Bitcoin in achieving a wider and significant acceptance in the market is that the innovation is not allowed and backed by many central governments and regulatory authorities and not considered as a legitimate tender. The central banks and regulations of many states around the world advise the potential or actual users to show more cautiousness and awareness to the risks associated with crypto based currencies like Bitcoin transactions because of the vulnerability of digital wallets to theft or loss. The competing and often conflicting mining protocol standards and the lack of significant collaborative solutions and the potential problems of vulnerable computer and internet infrastructure have challenged Bitcoin to achieve a significant global adoption.

FinTech's Big Promise- Frustration with the status quo is an oft-cited impetus for FinTech. FinTech innovations are early always predicted to yield some efficiencies and useful opportunities, particularly in transaction processing, financial analysis, and the development of alternative investment vehicles or business methods. Efficiencies are generally predicted to be the product of disruptive disintermediation, the reduction of transaction processing, advice or facilitation by agents.23 The deployment of computerized telecommunications usually permits FinTech entrepreneurs to claim faster, democratized and more accurate operations. Existing market failure or sluggishness are also targeted by FinTechs. In other situations, FinTech leads to re-intermediation. Alternatively, some regulatory-oriented FinTechs, particularly those inspired by expanding existing data to become big data, amplify transparency, attenuate market failure or produce positive externalities for society. Recognition of the alternating causality among FinTech and big data analytics and other computational techniques suggests FinTech is a compelling domain for big data analytics. Stated alternatively, as an organizing principle, a big data analytics lens provides a unique approach, fundamental to the development, understanding and regulation of FinTech not well recognized in existing literature.

FinTech's Delivered Effects- It is hardly surprising that some FinTech mechanisms externalize their design flaws, their opacity and obscurity, or their malfunctioning to contribute to various types of market failures. Most of the major FinTech watersheds in the 20th and 21st Century history of securities and commodities regulation, banking regulation and insurance teach that FinTech almost always deserves a wary eye. Too often, FinTech is arguably intended to skirt regulation or avoid regulatory costs. It is hardly surprising that FinTech entrepreneurs are initially seldom very aggressive to bolster their emerging industry's reputation by seeking reasonable regulation. Various forms of FinTech start with stealth operations that in turn trigger abuse and repercussions, caused by their too often incalculable and uncertain risks. In most instances, big data can play a key role in resolving FinTechs unintended consequences. Furthermore, FinTech's often decentralized architecture (P2P, distributed nodes, cloud storage) operates by defying jurisdiction of tougher and hi tech regulators. This creates a classic "race to the bottom" as lax regulatory hosting venues attract FinTechs. The result is a heightened systemic risk for most all markets for financial services. FinTech nearly always imposes regulatory challenges as a result of these substantial influences. Therefore, to avoid the harmful societal externalities of FinTechs, an anticipatory FinTech regulatory dimension is advocated here using provisional ontologies. This model requires a big data model and urges adoption of a big data dimension on FinTech development and central regulation. Both champions of FinTech innovation as well as FinTech skeptics and financial market regulators can benefit from the development here of a generalized model deploying big data and analytical methods. Not surprisingly, some FinTechs are creations of government. These are largely transparency regimes using standardized disclosure, such as EDGAR, xBRL, ISO 20022, or the Dodd-Frank swap disclosures.25 Still, FinTechs often develop long before understanding by regulators is achieved or regulators can develop effective regulatory balance.26 Delays between FinTech development/deployment and effective public policy response development/implementation constitutes a form of regulatory lag.

Summarizing a FinTech Ontology- FinTech is substantially new, its popular descriptions are largely established by promoters and adherents of a few recent FinTech trends: crowd-funding, blockchain and cryptocurrencies, and robo-advising. As with any popular theme attending a field's development, "what has been done lately" commandeers the most attention by attenuating almost all other context. By contrast, this paper runs counter by offering historical context of innovation in financial services permitting a different taxonomy: money and payments, contracts and financial claims structuring in instruments, intermediation and syndication, disclosure, standardization, analytics techniques - financial and creditworthiness analysis, and the embodiment of innovations in intellectual property. In addition, we adhere to the traditional U.S. visions of financial services subfields of commodities and foreign exchange, commercial banking, investment banking and insurance. As to the next big thing that may usher the transition from the fourth ICT era into some hypothetical fifth era, currently the most compelling candidate watershed factor is AI. If reliably useful, AI can be developed that significantly impacts many trenches of financial services, the fifth FinTech era may dawn.184 However, that time has not yet come despite some limited AI success in the fraud and intrusion detection components of a few FinTechs. AI is hugely complex and although many brilliant minds and powerful computer capabilities are diligently deployed to AI's success, AI progress must await resolution of its data interoperability problem. While the taxonomy developed here acknowledges AI could develop a long and promising ascension, FinTech still awaits any significant transformational impact from AI, despite repeated assurance from AI's adherents of it's transformative imminence. Any AI revolution to a fifth FinTech era seems more likely to mature in the medium term future.

Simple Taxonomy for FinTech Big Data- Three major types of information comprise FinTech big data.190 This provisional taxonomy will initially guide the clearance and incentivizing of these data to facilitate big data analytics. The three types are;

(1) data that directly enable internal control of active financial services operations,

(2) data that enable the monitoring of externalities produced by activities of FinTech participants and intermediaries, and

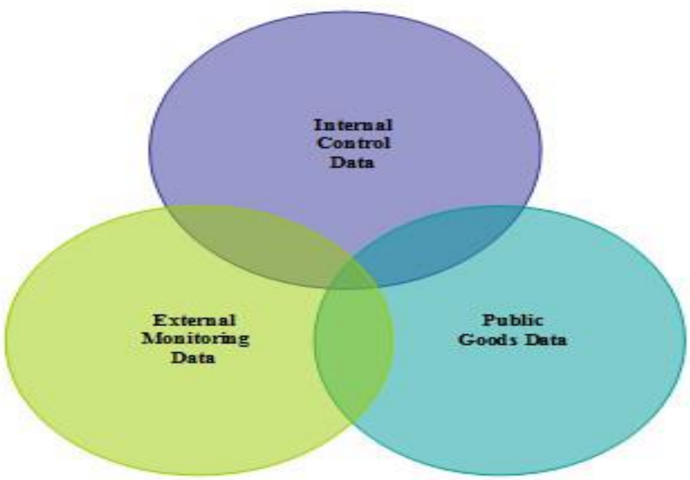
(3) public goods data.

Internal Control Data- Internal control data are typically produced by any party, its employees or third parties. Internal control data are needed to optimize most all financial services decision-making and consequent actions. Generally, these data are sourced in-house or provided by independent outsource service organizations.

Externalities Data- Externalities data are produced by stakeholders, employees or third part service providers/organizations. For example, data aggregating to financial disclosures of publicly-traded companies is initially recorded by internal bookkeeping staff, provisionally audited by internal auditors, then aggregated for financial or tax reporting by internal accounting personnel, all typically are employees. These data are then subject to non-employee activities - audit and attest by independent auditors, assessment by ratings firms, securities analysts and the financial press. Regulators may have regular periodic access to such data (e.g., financial reports, tax returns) or episodic access during investigations, enforcement actions, litigation or audit. Watchdogs and the press interpret data from various investigatory sources to constitute externalities data.

Public Goods Data- Information as public good data generally serves to enhance public monitoring and can be sourced from internal, external and open sources. While financial performance data of publicly-traded companies are generally considered public goods, these data tend to oscillate between free public access vs. proprietary accessibility only as purchased or subscribed to under a data integrator business model. The relationship among the three is depicted by the seven regions revealed in Figure 5.

Figure 5: Information Production Taxonomy



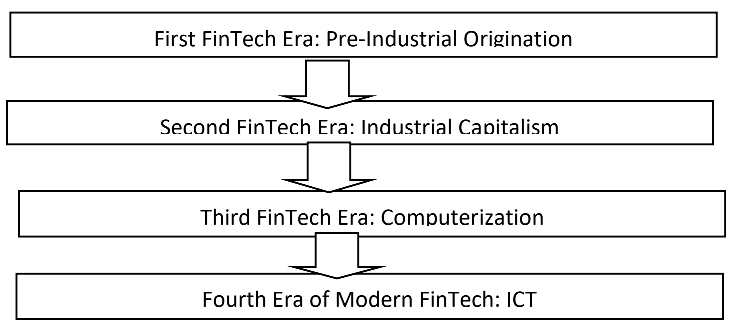
Compliant with the standards, standards attract independent innovation to produce or use the standardized data, competition among suppliers of data and analytical applications usually reduces cost, incents quality control competition, and permits improvement innovation. Of course, monopoly ownership of data and data standards can lock-out competition, risks stagnation and reduces the scale of data sharing, a potential oligopoly. On balance, data standardization potentially increases monitoring by independent observers, while arguably increasing comprehensiveness and the discovery of key conditions, relationships, and phenomena. Standardization encourages the ubiquity of sensors and enables sensor fusion, an analytic technique that expands analytical opportunity. Standardization also encourages both consistency in analytics as well as innovation in analytics. Consider how thresholds of big data analytics in the creditworthiness area have generally moved towards some consistency in suspicion, corroboration, probative value of circumstantial evidence, and the sufficiency of direct evidence. FinTech big data miners can be expected to provide analyses that aids in the development, testing and justification of regulatory controls over FinTechs. This dimension could also empower victims of FinTech externalities with at least circumstantial evidence that supports ancillary control mechanisms such as private rights of action.

Ontology of FinTechs from a Chronological viewpoint- A provisional chronology of FinTech from the pre-FinTech ancient/medieval era, through U.S. history in the 19th and 20th century, to the post-war modern era, and ultimately to the modern FinTech period provides an opportunity to trace FinTech's technological development history. This analysis also marks key transformative change points and their disruptive challenges to FinTech public policy. Other scholars have proposed typologies, some casting them as FinTech business models. For example, Lee and Shin argue that current and proposed FinTechs should be divided into six discrete business models: (1) payments, (2) wealth management, (3) crowdfunding, (4) lending, (5) capital markets, and (6) insurance.

They predict FinTech will face the greatest challenges in the areas of investment-management, customer-management, regulatory challenges, technology-integration, security issues and privacy issues, and risk-management. The Partial FinTech Chronology depicted in Figure I, illustrates the difficulty of taxonomy development, given an accelerated pace of technological change.

Four Eras of Fintech: Tracing FinTech through Four Eras- After the pre-FinTech era of ancient through medieval times, we divide FinTech into three modern eras that follow three major technological watersheds: first, electrical analog telecommunications, second, computerized recordkeeping, and third, fusion of these first two into ICT deployed or under development in the current era. The impact of FinTech, developed throughout the 20th Century, is spurred significantly by innovations and ubiquity of telecommunications and computational power. FinTech's second stage, the first of the modern era, roughly tracks industrial capitalism. Much of FinTech innovation was based on analog electronic communications developed in the 19th century - telegraphy and telephony. These twin innovations spurred significant FinTechs by improving communications that have extended well into in the 20th century. Near instantaneous electronic communications made financial markets and services accessible from/to across the U.S. and around the world. Major financial markets were enabled to more permanently coalesce into a few of the world's moret influential developing venues, including, New York, London, Hong Kong, Frankfurt,Tokyo, and others. FinTech's second modern era began to transition by the 1970s as computer recordkeeping finally invaded the "back office" of insurance, commercial and investment banking. Computerization also permitted statistical risk analyses, important in risk underwriting and financial analysis. This era also witnessed the development of electronic order processing, program trading, electronic corporate democracy, and electronic financial disclosure.

Figure 6: Four Eras of Fintech



First FinTech Era - Pre-Industrial Origination- From ancient times to the industrial revolution, financial technologies developed slowly, often spurred by conflict and in relation to religious activities. At the time of these FinTechs were introduction, each was capable of producing big data for that time. Considering the difficulties in recording, storage, communicating and analyzing data using technologies of the era, FinTechs created what becamr big data of that time in history. Most FinTechs originally developed during this period persist in some form today and continue to be big data driven. Much of the ancient FinTech successes developed in ancient Greece and Rome, with the Crusades, and the rise of mercantilism also influential. Stabilization of the enduring FinTechs was guided by a few, large nation states, particularly imperialist nations of Western Europe which colonized the New World such as the Dutch, Italians, English, Spanish, Prussians and Portuguese. Financial services are the infrastructure for the development of trade and industrial-based commerce, the major growth of which developed in the first two millennia AD. Four enduring FinTech first principles were developed during this origination era, then were extended and refined from ancient times through the middle ages. Nearly all modern variations of financial services are established from these origination era starting points; (1) Contract, (2) Money, (3) Intermediaries (4) Organized Exchange (auction) markets, and (5) Legitimation of Debt.

These five pillars are the bedrock institutions that support and expand into voluntary negotiated exchange under contract, evolution from barter to recognition of money as secure and standardized medium of exchange, physical security for financial assets and services by third parties, advanced quality control for recordkeeping, correspondent banking, syndication networks, and standardized (auction) market mechanisms.

Second FinTech Era - Industrial Capitalism- The second era is the first stage in the modern era, roughly tracking the industrial revolution through to the mid-20th century. Analog electronic telecommunications that developed in the 19th century, telegraphy and telephony68 were most influential. This disruption permitted near instantaneous electronic communication to and from centralized financial markets. Communication tied together geographically-separated exchange markets and provided immediate visibility to supply, demand, completed transaction prices, and trading volume. At first, all these and other data derived there from were recorded by hand and, too often, haphazardly at best, most likely due to cost, delays, technical infeasibility, failures to embrace their social utility and a desire for opacity by some participants. However, advances in recordkeeping remove most of these limitations permitting the accumulation of this information

into big data. This environment produced new financial services to accommodate higher volumes of speculative investment, permit entrepreneurs to gain better access to capital raising, and expand the pools of potential investors and opportunities. The democratization of investments also functioned to undermine banking as the solitary investment opportunity for many individual savers who could transition to become investors. Many new financial market participants gained access from/to geographically isolated areas. Major financial markets more permanently grew, yet coalesced, creating a somewhat geographically dispersed financial services infrastructure that magnifies the development of an integrated exchange market despite dispersed venues. This network eventually approximates a true *national market system* (NMS).

Following financial services were established from the second era; (1) Syndication (2) Financial Exchanges (3) Electronic funds transfer (EFT) (4) Regulation (5) Disclosure Regime & its Intermediation

Third FinTech Era – Computerization- The third FinTech era, the second era of modern times, herein is called the computerization era. The start of this era begins with the electronic computerization of financial records. For much of FinTech, this watershed was probably reached when Wall Street was forced by the avalanche of increased trading records retained on paper to automate recordkeeping in its "back office." Exchanges outgrew their collective character as agents of competing members and banded together into self-regulatory organizations (SRO) capable of metering, retaining, monitoring and supervising member activities based on their separate big data collections. The FinTech big data relationship among the major FinTech sectors defined here is becoming clearer: recordkeeping that populates big data accumulations, analytics, disclosure, regulation, institutions and trading strategies are inextricably linked in feedback loops. Big data drives analytics, analytics inspire models, models produce propositions, propositions inspire recommendations, recommendations imply actions, actions are manifest as innovations embodied as trading strategies, such innovations are often implemented as transactions, results are measured then monetized or deployed against activities of others, institutions are impacted by results, and institutions restart one or more of these cycles. Following financial services were established from the third era;

(1) Automated clearing houses (ACH)

(2) Payment Card Ascension

(3) Countertrade

(4) Disclosure repositories

(5) Analytics Techniques

(6) Intermediation

(7) Electronic Data Interchange

(8) Trading Strategies

(9) Financial Institutions

Fourth Era of Modern FinTech – ICT - The fourth era of FinTech is upon us, starting roughly in the 1990s, persisting through today and most likely extending into the near to medium term.127 It is defined by the ubiquity of ICT - a fusion of computerization with rapid, high-throughput telecommunications of data, images, text and other data forms. Furthermore, at least four other technologies enable this ICT era; (1) well-connected, secure and reliable Internet, (2) trustworthy and economical cloud accessibility for posting and accessing large data sets, (3) robust private networks, and (4) interoperability based on highly functional ICT standards. Finally, some might assert that AI contributes significantly to the current ICT era, however, solid evidence of this as a key watershed remains inconclusive. Following financial services were established from the fourth era; (1) ICT enabled Payments (2) Toll Tags (3) Check Truncation (4) Electronic Payment Systems.

4. BIG DATA ANALYTICS FOR FINTECH

While varying definitions of big data exist, the stricter vision not advocated here creates such a narrow scope, that it would remain useful only at the technical frontier of analytics for business – here is no big data unless the "accumulation of data that is too large and complex for processing by traditional database management tools and conventional computer softwares." But an examination of big data analytical methods and big data scholarship show that statistical techniques, standardized data structuring, and increasing storage capabilities, relegate such inhibiting conceptualization to narrow audiences.

Advances in data processing, storage, association, and structuring are not only foreseeable but must be anticipated. Thus, past or just now current feasibility of using big data, an eternal technical barrier, is steadily resolved by advances from a set of converging disciplines focused on making big data analytics feasible. Indeed, the statistical analysis tools community provides a conceptualization of big data much nearer to the definition used here, Big data describes the huge volumes of data – both structured data as well as unstructured data – that is captured and processed on a daily basis. Big data analytics actually becomes feasible roughly paralleling computer developments under Moore's Law,35 tracking advances in bandwidth, software tools, data storage and processing capacity. Moore's law and evolving business practices suggests that four phenomena propel big data analytics;

1. Ever decreasing data storage costs,
2. Ever increasing processing capabilities,
3. Demand for analysis of big data, and
4. Apparent usefulness of predictions made thereon.

It is argued here that nearly all past and present FinTech innovations eventually triggered a deluge of new and more complete data. New FinTechs required novel techniques to recognize where and how to capture that data, new communications methods were enabled to transmit the data, new storage methods developed to warehouse and organize the data for useful retrieval, and new analytics are tried and tested for validity of the meaning derived herefrom. In the next section, many FinTechs are evaluated in light for their contribution to financial services viewed through the big data analytics lens.

4.1. Centricity of Big Data in Fintech

A select recitation of FinTechs through history is presented here for three purposes:

First, a long list stimulates a more expansive view of what constitutes FinTech and its successes and failures. Such inquiring dimension is needed to support the main thesis, that big data analytics occupies a centrality to FinTech.

Second, a more comprehensive list advances this investigation from the mere, transitory "hot topics" thesis of most popular FinTech literature to generate a more enduring understanding. The FinTech classification scheme developed here assists in organizing interest in current FinTechs and better prepares the analyst to anticipate and appreciate future FinTechs.

Third, analysis of multiple, significant instances, permits induction of more generalizable models. Of course, new clusters of FinTechs may emerge in the future, but many recent FinTechs are simply the accomplishment of traditional financial services using alternative, updated methods.

4.2. Anticipatory FinTech

FinTech data is voluminous, so it is a huge task to develop any single model to catalog and marshal, gain rightful access, standardize formatting for interoperability, assure meaningful maintenance through timely updates, authenticate, and access quickly and reliably using standardized data structures. Only small subsets of FinTech data approach this big data reliability plateau. Therefore, any model headed for success in predicting FinTech direction using big data must develop these aforementioned access reliability and analytics methods. Indeed, new data will come from newly initiated repositories, new sensors and collection points, intermediate results of new analytics, and new FinTechs themselves. As the FinTech litanies in the eras discussed above suggest, there are trading and transaction records, financial statements, dispute settlements, innovation designs, expert and newsworthy reporting, and the underlying papers supporting all the above. Some of these data are proprietary, private, confidential and remain secret. Many of these data are already produced and either made accessible due to some regulatory scheme or are produced under "for profit" business models. Therefore, not all FinTech big data are financially self-supporting. Those unable to sustain a business model are not likely to be reliably available without regulatory mandate or subscription access. FinTech data are produced and primarily utilised by very different domains. These domains are very deep silos of expertise that may ever be well integrated. First, there must be developed inventories of FinTech information from various sources. Next, provisional relationships and links among these data sets must be developed from various financial market literatures, information vendors, public disclosures and regulatory data repositories. Third, proposed analytics must be tried and tested for their explanatory or predictive validity. A key challenge to effective FinTech big data arises from the jealously guarded proprietary information and the opaque financial performance of closely-held firms. This is a never-ending, continuous quality improvement (CQI) process - big data requires constant replenishment, redesign and revision to maintain useful analytics.

4.3. Big Data Adoption Methods in Fintech: Direction Anticipation Crypto

This section is intended to demonstrate the feasibility of the anticipatory FinTech model by applying it to one of the most actively discussed and current ICT era FinTechs: blockchain distributed ledger on which cryptocurrencies and smart contracts are based. This exemplar implies several FinTech sectors discussed in the litanies above: intermediation, payment systems, the under-banked, securities/commodities/foreign exchange trading, smart contracting and novel instrumentation, FinTech standardization, security and privacy, and forensics. All these FinTech sub-fields have clear implications for both innovators and regulators. For example, cryptocurrencies show promise to enhance money-laundering. Generally, this is a bad thing. Cryptocurrencies may also enhance the big data analytics of anti-money laundering enforcement (AML) as more complete cryptocurrency transaction records are based on enhanced blockchain forensics. The latter is probably a good thing. The ICOs of recent years run afoul of many domains of the securities regulatory regime. These include: fraudulent get rich quick and Ponzi schemes configured as unregistered initial public offerings or noncompliant private placements, payment for securities using cryptocurrencies, prospectus-like offering documents masquerading as (boiler plate) “white papers,” cryptocurrency trading platforms amounting to national security exchanges, Dodd-Frank swap reporting violations, sales of privately placed securities with unaccredited investors, violation of various broker/dealer regulations, fraudulent statements in disclosure and promotional documents, use of cryptocurrencies in the securitization of various assets and celebrity promotional endorsements, IPO rule violations, fraud by public companies with various crypto currency assets, lines of business in exchanging cryptocurrencies for traditional fiat currencies or debit cards, theft of cryptocurrencies asset holdings, and illegal crowdfundings. The number of cases being pursued by the SEC and its sister agencies has increased over the years. Many cases hinge on how the initial coin offering resembles the investment contract catch-all of a security. First, *Howey* constrains FinTech from assuming any claims structuring that bear family resemblance to securities, contracts requiring an investment of money into common enterprises, promising profits primarily from others’ efforts.

4.4. Technology Diffusion Theory

The three dimensions of IT adoption: IT planning, actual IT implementation, and IT diffusion were studied. Each one of the three dimensions is necessarily important for the success of the following one in a mutually dependent relationship. IT planning involves the alignment of the strategies to present and future operations and vison of the organization. IT implementation includes the overall efforts for selecting and implementing new technology solutions, developing necessary skills, and measuring the effectiveness and efficiency of new systems. IT diffusion is capable of managing change and the adoption and diffusion of new technology solutions by the organizational members.

IT deployment: IT planning - This phase of IT planning provides strategic guidelines for IT deployment based on organizational goals. IT planning consists of the first three phases of Rogers’ five-stage model of the implementation process, which are; Knowledge – Persuasion – Decision. The IT planning dimension also covers the first two stages of Cooper and Zmud’s six-stage model of the IT implementation process, which are; Initiation – Adoption.

IT implementation- The process in which it is assured that the new system is operational, and then users are allowed to take over for use and evaluation. IT implementation includes almost every stage –start to end- that it passes through from the purchasing or developing, until the system is achieving its goals for the members as well as the organization.

IT implementation includes the fourth stage of Rogers’ five-stage model: Implementation – Compatibility – Complexity – Trial ability.

Adaptation- The process of adaptation ensures that the IT solution being implemented successfully and the training of the team is comprehensive, the IT solution is ready to take over. The successful goal oriented implementation of IT in a business organization depends on several interdependent factors. The planned goals of IT implementation should be realistic to get the total commitment from the employees of the organization. According to Shenhar and Levy , both the technical and social systems that contributes the organization, any approach to IT implementation must take into consideration to be successful.

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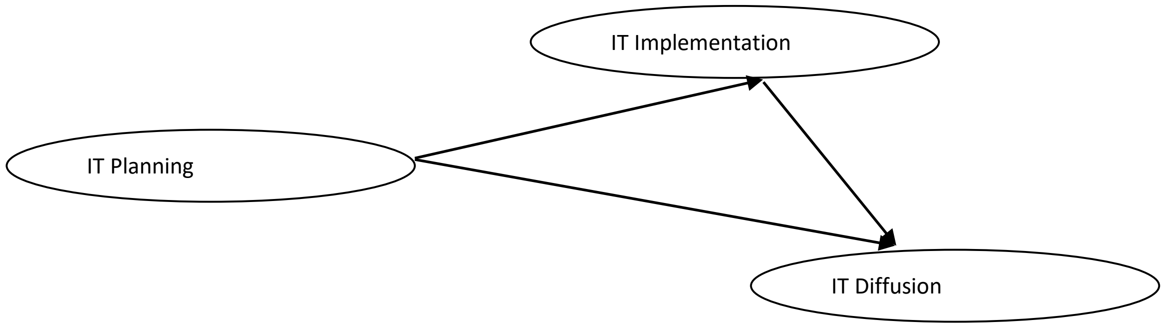
Figure 7: The Widespread IT Deployment Model



IT diffusion IT diffusion includes the last three stages of Cooper and Zmud's six-stage model of the IT implementation process: Acceptance - Routinization - Infusion

5. RESULTS

Employees at fintech companies were requested to fill the survey questionnaire (100 were distributed, 90 collected, 88 selected) with questions including IT-planning, IT-implementation, and IT-diffusion. The constructs were taken from the existing scale from the literature. 88 completed questionnaires were returned (98% response rate). Data was collected to identify the respondent's designation (management/employee) and experience with fintech companies. Of the 88 respondents, 68% were engineers; approximately 27% were managers The average experience of the employees was 3 years, ranging from 1 to 6 years. For presentation and interpretation, the analysis of collected data was divided into three groups:

1. IT-planning.

2. IT-implementation.

3. IT-diffusion.

IT planning: Of the eleven separate IT planning issues, adequate training and resistance to change were significant, indicated by 50% and 45% of participants, respectively. Rapidly changing technology (44%) and existing systems (40%) were other significant concerns, reflecting the decision-dilemma faced by planning managers: how to leverage current IT investment in line with innovations.

IT implementation: The major issue out of nine was quick solutions, indicated by 50% of participants. Politics, internal/external (45%) and emerging technologies (45%) were other significant concerns.

IT diffusion: Of the ten separate issues, technology challenges and attitude to change were the significant ones, indicated by 60% of the participants. Security is also significant concern (55%).

Table 1: Varimax-Rotation (Three-factor proposition for IT-planning issues)

IT planning	Factor 1	Factor 2	Factor 3
Emerging technologies	0.68	-	-
Standardization	0.53	-	-
Technology value	0.70	-	-
Timeframes and scheduling	0.83	-	-
Written procedures/guidelines	0.87	-	-
Politics, internal/external	-	0.88	-
Organizational culture	-	0.87	-
Interdepartmental coordination	-	-	0.90
Percent of variance illustrated	3.63	1.75	0.90

Table 2: Varimax-Rotation (Three-factor proposition IT-implementation issues)

IT implementation	Factor 1	Factor 2	Factor 3
Adequate training	0.50	-	-
IT budgeting allocation	0.66	-	-
Interdepartmental coordination	0.50	-	-
Written procedures/guidelines	0.74	-	-
Timeframes and scheduling	0.82	-	-
Standardization	0.75	-	-
Rapidly changing technology	-	0.69	-
Individual IT expertise	-	0.87	-
Resistance to change	-	0.70	-
Adequate IT staffing	-	-	0.91
Interdepartmental coordination	-	-	0.63
Percent of variance illustrated	3.98	2.27	1.54

Table 3: Varimax-Rotation (Three-factor proposition IT-diffusion issues)

IT diffusion	Factor 1	Factor 2
Perceived benefits	0.67	-
Compatibility with systems	0.78	-
Security concerns	0.70	-
Management participation	0.71	-
Attitude to change	0.68	-
Effort required	0.70	-
Previous experience	0.64	-
Risk taking	0.68	-
Technology challenges	0.81	-
Time investment	-	0.92
Percent of variance illustrated	6.42	0.92

Factor analyses (FA) was conducted to understand the underlying factors.

Factors identified for IT-planning

Factor1 (Innovation issues): Emerging new-technologies, standardizing, value of technology, time-frames, scheduling, and documented procedures and guidelines.

Factor2 (Strategy issues): Timeframes, scheduling, and documented procedures and guidelines.

Factor3 (Intra-organizational issues): Coordination among departments.

Factors identified for IT-implementation

Factor1 (Deployment issues): Comprehensive training, IT budget allocation, coordination among departments, documented procedures and guidelines, timeframes, scheduling, and standardizing.

Factor2 (Skills update issues): Agile technology, IT expertise of the members, resistance.

Factor3 (Business analysis issues): Proper IT staffing, coordination among departments.

Factors identified for IT-diffusion

Factor1 (Ease of use issues): Perceived benefits (by users and organization), compatibility with existing systems, security issues, management willingness, acceptance for change, required effort, experience, ability to take risk, and challenges of technology.

Factor 2 (Learning period issues): Time commitment and investment.

Once the process of data reduction was done, the aim of determining the correlations among IT planning- IT implementation- IT diffusion issues was accomplished. Regression analyses were done to find the nature of the correlations, if any. The results of the tests indicated the significant associations between IT-planning (innovation issues) and IT-implementation (deployment issues) factors. Further, IT-planning issues were also significantly correlated with IT-diffusion issues. IT-implementation issues were found to be significantly correlated with IT-diffusion issues. The results indicated that still more focus is expected in the case of novel technologies which can help the successful deployment and diffusion of new technology.

Hypothesis testing results

H1: Significant factors are there in IT-planning.

H2: significant factors are there in IT-implementation.

H3: Significant factors are there in IT-diffusion.

H4: Significant relationships are there among IT-planning, IT-implementation and IT-diffusion.

Hypotheses were confirmed through factor analyses (FA) and regression tests.

Table 4: Regression Analysis (Implementation as a Function of Planning)

Dependent variable

Deployment issues	R	R square	F
	0.70	0.49	41.6
Innovation issues b	Beta	p-level	
	0.71	0	

Table 5: Regression Analysis (Diffusion as a Function of Planning)

Dependent variable

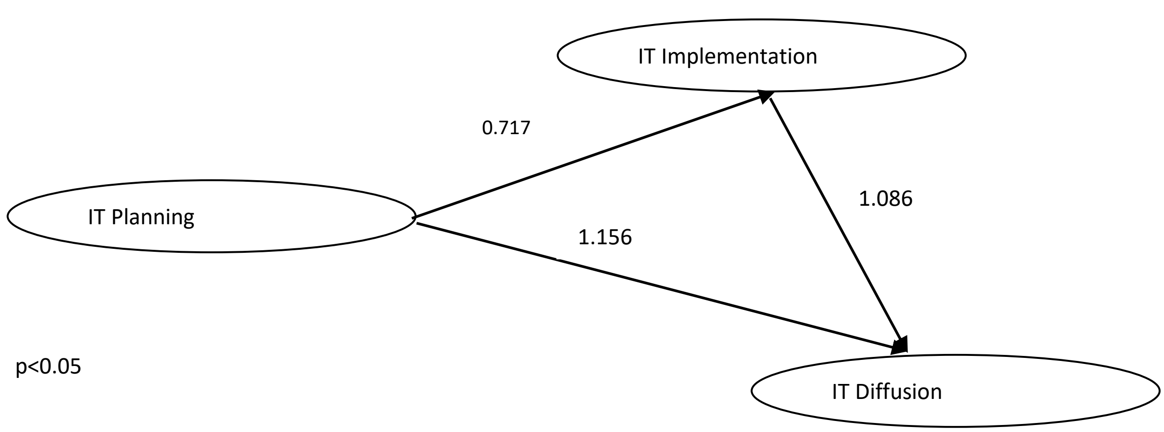
Deployment issues	R	R square	F
	0.73	0.54	49.4
Innovation issues b	Beta	p-level	
	1.15	0	

Table 6: Regression Analysis (Diffusion as a function of implementation)

Dependent variable

Ease of use issues	R	R square	F
	0.70	0.49	40.7
Innovation issues	Beta	p-level	
	1.08	0	

Figure 8: Results of the framework with p values



6. CONCLUSION

This paper provisionally defines FinTech broadly and integrates big data analytics to inspire FinTech innovation, understanding and regulation. The FinTechs receiving most contemporary, the "cool" technologies, largely dis-intermediate financial services, obscure rogue transactions and disrupt financial markets. However, FinTech is actually much larger than contemporary practice suggests. Indeed, FinTech may be a superior theme to understand the chronology and regulatory-delay in the public-policy reaction to financial services externalities. Big data is a useful lens to understand FinTech, develop innovations in the FinTech sector, and impose public-policies that encourage useful and profitable FinTechs and discourage the harmful ones. Contemporary experience demonstrates that both market-failure and social-engineering impact FinTech innovations. Most FinTechs throughout history achieved both (1) held unrealized big data potential when initially introduced and (2) now have inspired the application of big data analytics. Furthermore, in the future, FinTechs can be better designed using big data analytics, better understood for their intended and unintended consequences using big data, and more successfully regulated using big data forensics. Therefore, big data inherently incentivizes, exposes and resolves FinTech challenges. The motive of this study is to describe, review, and reflect on big data analytics in fintech sector. The paper first defined big data to consolidate the different discourse and literature on big data. We also reflect the point that predictive-analytics (with structured data) overshadows other forms: descriptive and prescriptive analytics (with unstructured data) which constitutes more than 90% of big data. We also reflected on analytics techniques for unstructured data: audio, video, and social media data, as well as predictive analytics. In the analysis and testing part we also performed the testing of the IT diffusion model which concludes that there are significant relationships among IT-planning, IT-implementation and IT-diffusion.

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