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Strategic Financial Intelligence: Using Machine Learning to Inform Partnership Driven Growth in Global Payment Networks

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Abstract

Throughout this extensive study, we present a thorough analysis of partnership-driven growth within payment networks. We provide an in-depth and detailed explanation of the diverse dataset, which comes from the global payment messages and includes a meticulous examination of the processing and matching pipeline that is necessary to effectively coalesce company and network data from multiple varying sources. We then benchmark the significant impact on network profitability by thoroughly evaluating transactional variables, firm fundamentals, and the intricate structure of the network.

Using various attributes related to node importance, such as the number of unleashed partnership opportunities, internal and external centrality metrics, and community structure, we diligently develop customized indicators designed to measure how different types of corporate actions can enable firms to fill their liquidity needs within the network more efficiently. To suggest how financial intelligence and insights could also be translated into strategic action, thus preparing the grounds for accurately predicting whether firms would predominantly benefit from internal network adjustments versus external organizational reconfigurations, we subsequently turn our attention to advanced machine learning models.

In conclusion, we summarize and discuss potential directions and promising avenues for future research in this vital area. This not only highlights the importance of evolving payment networks but also the opportunities that arise from strategic partnerships and innovative technological implementations that can drive growth and stability within financial ecosystems.

Keywords: *Partnership-Driven Growth, Payment Networks Analysis, Global Payment Messages, Transactional Data Processing, Network Profitability Evaluation, Firm Fundamentals in Payments, Network Structure Optimization, Node Importance Metrics, Partnership Opportunity Analysis, Centrality Metrics in Finance, Community Structure in Payment Networks, Corporate Actions in Liquidity Management, Financial Intelligence Insights, Strategic Network Adjustments, Machine Learning for Payment Networks, Predictive Financial Modeling, Internal vs. External Reconfigurations, AI in Financial Ecosystems, Payment Network Stability, Technological Innovations in Finance.*

I. INTRODUCTION

Global electronic payments have grown to dominate the electronic channels for personal and company funds movement, bringing benefits of economic growth including asset liquidity, transparency, and enabling commercial activity. One of the main complexities in global payment systems is posed by the cross-border flow, with operational and execution costs akin to, and often higher than, those encountered when mail correspondence or freight shipments are executed in the physical world. Despite the criticality of the global payment network structure for efficient market flow performance, little is known about the architecture, trends, and ultimately the evolution of network traffic or capacity.

The research presented in this paper is a collaborative research and development project with a leading global banking and financial services company, where we investigate the intersection of operations, marketing, and financial intelligence activities to deepen the bank's understanding of its global payment infrastructure. We use distinct data mining and machine learning techniques to assess the influence of node and edge perspectives – identifying positioning to shift center and feeder positioning to implement shifts at the edge of optimization actions within the payment business. The practical research outcomes that are pursued include the generation of distinctive global payment partner scores employing a feature-based unsupervised learning approach, detecting outliers in the business hierarchy, and linking the bank's brand affiliation to its choice of global partners. We also utilize the developed cloud-based platform to assess network effect performance in new market entry planning and execution, within a described four-step activation framework.

- *Setting the Stage: The Importance of Financial Innovation*

Innovation in financial services is imperative. It drives money and credit, transfers payments, provides liquidity and compounding, channels saving and investment, steers portfolios, and adjusts risks. It addresses the foundational institutional needs of monetary exchange, banking services, and capital exchange. Finance drives globalization, advances economic development, and assuages economic catastrophe. Financial innovation overcomes coordination failure and catalyzes transaction economics. Financial infrastructure represents the prime target of instrumental reform necessary for financial inclusion and competitive market economies. Innovative financial institutions discovering and facilitating the formation, exchange, and payment of money and value are organized in partnership arrangements, each party contributing specialized capabilities that leverage network economies. With unified brand representation, institutions seek ways to leverage these partnerships as they embark on growth strategies. Strategic intelligence can guide their efforts. This text applies the methods from machine learning to train algorithms to provide strategic financial intelligence about key drivers of economic value and risks associated with growth in a global partnership-driven network in the payments industry.

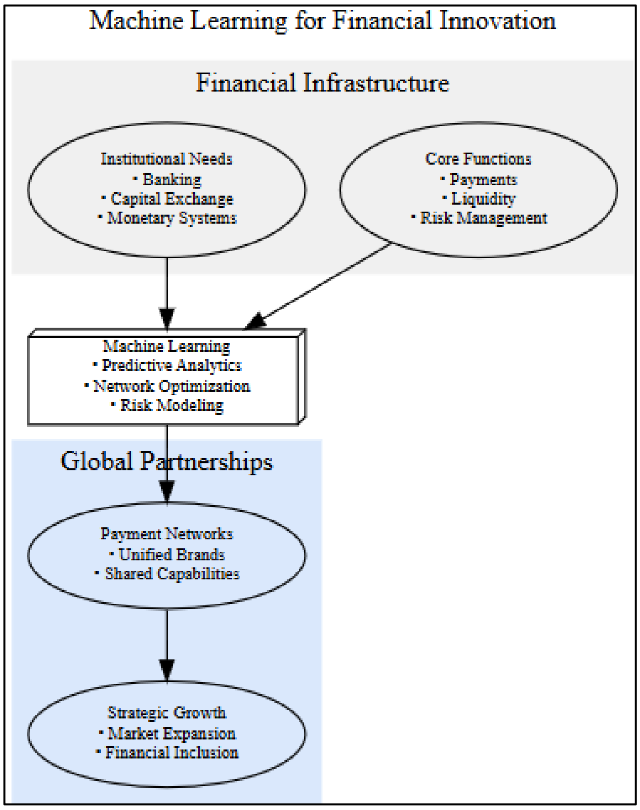

Fig 1 Machine Learning for Financial Innovation

- *The Evolution and Impact of Financial Innovation*

Economists have observed that the evolution of financial intermediation has historically happened in close synchrony with advances in financial technology, as a general phenomenon known as the co-evolution of technology and finance. Innovation in financial technology often emerges in periods of considerable strain in the financial system, as solutions to meet critical needs, as well as in less stressful periods where focused investment can turn opportunities into capabilities. Over time, the development of new financial tools and services has a demonstrated effect: financial development has a causal relationship to economic growth.

Certainly, the impact of financial technologies is not uniform, and the hopeful expectation of economic gains does come with potential risks to stability and inclusion. Nevertheless, an economy that can tap into the potential contribution of financial technologies, including those that are improvements in the distribution of existing tools, can be expected to experience improvements along several dimensions: people carry out more efficient economic transactions that increase their utility; companies are more effective and better rewarded for the effective use of financial capital; and banks are better able to support the real economy with a reduced risk position. With the significant promise of these technologies comes compelling cases for data-driven research in the field, as a necessary precursor to the strategic deployment of these methods in the productive pursuit of liquidity and stability goals.

II. UNDERSTANDING GLOBAL PAYMENT NETWORKS

Global corporations engaged in cross-border value exchanges want confidence that promised payment will flow at the expected time. Payment is a foundational element in conducting business around the world. In 2015, payments received and initiated by these market participants, excluding domestic and intercompany transactions, accounted for about 23% of gross capital flow. Yet the institutional mechanisms that physically deliver payment between parties are quite nascent, especially when compared to the sophistication of the goods and services these payments fund. Historically, global payment networks have positioned themselves primarily as mutual agreement organizations, fostering a neutral framework for the exchange of monetary obligations. The connectivity and support for transaction types enabled in the payments infrastructure have been debated by industry participants but are infrequently explored in economic research. Progressive real-world risk management and innovative solution development have been executed on financial intelligence. Clearing houses and global payment networks have been proactive, working closely with a broad spectrum of network participating members to make strategic use of the financial data they enable.

These data partnerships, encompassing more than 75% of global cross-border payment flows, represent a relatively unexplored opportunity area. A framework for partnerships aggregating private firm data to enable financial intelligence using machine learning methodologies in the context of global payment networks is presented. Actionable outcomes generated from machine learning feature relationships demonstrate clear potential for enhanced transaction processing and the development of clients' payment strategies related to network disputes. Organizations with a global geographical footprint, including those established for the facilitation of international cross-border commerce, are most likely to benefit from the strategic alliance. The insights are especially beneficial for developing financial soundness and the confidence necessary for driving growth.

Equation 1 : Revenue Growth from AI-Driven Partnerships

$$R_{\text{growth}} = \sum_{i=1}^{n} (P_i \times C_i \times U_i)$$

R_{growth} = Total revenue growth,

P_i = Partnership revenue contribution per entity,

C_i = Customer acquisition rate from the partnership,

U_i = Average transaction value per user.

- *Overview of Payment Systems*

Banks, businesses, and individuals use payment systems to transfer funds with finality, settle obligations, and meet demand for money. Domestic payment systems within regions and countries allow banks and businesses to pay each other with acceptable levels of convenience, security, and cost. These payment systems allow financial institutions to transfer value between each other by moving central bank money—currency held by commercial banks in special deposit accounts at the central bank or with the Central Securities Depository. Central bank money serves as the final payment for banks to settle their obligations with each other.

Payment systems also move commercial bank money—that is, deposit money that banks create at the time they lend to businesses and individuals. Payment services enable economic activities and the conduct of monetary and fiscal policies. They provide businesses and individuals with economic signals and services that let them use currency held at commercial banks in deposit accounts as a medium of exchange, unit of account, store of value, and method of deferred payment. A piece of money lets banks, businesses, and individuals make and receive payments by transferring deposit balances among each other. Domestic banknote and electronic payment systems rely on the efficient organization of licensed financial institutions, including deposit-taking banks and their customers. Banks and their merchants build special-purpose domestic payment systems and rely on central banks to press and distribute paper currency.

- *Key Players in the Payment Ecosystem*

In the payment cycle, large card associations occupy a unique and powerful position where they can assess substantial fees on traffic. These associations play a key role in routing transactions to issuing banks. The more powerful the issuer—measured by how often consumers generate these payments—the more valuable the acquirer, adding leverage to any game of chicken between these two parties. To play, debit and credit card issuers operate under contract with card associations. Issuers generally interact with both the users of their cards and other financial institutions. They have to sign up individual consumers to apply for and use their cards, for the profitable volume of card payments is a direct function of the number of cardholders. This proprietary customer management is why we can think of banks as owning credit card products, and card-issuing banks spend significant amounts on marketing to increase their cardholder bases. This cardholder base is their core asset.

In addition to several regional card networks operating around the world, banks offering credit and debit card products have options to provide mobile wallets and enable instant payments. These new offerings constitute an attractive deployment of customer acquisition costs given that the prospective cardholders already manage an account from the institution and conduct transactions through one of its online and mobile channels. In this way, incumbent payment providers can prevent their customers from transacting with a competitive supplier and turn off the opportunity for profitable interchange fee revenue created by the expansion in mobile, e-commerce, and cross-border payments. Recognizing the expanding opportunity in payments, several global technology companies and fintechs have developed digital payment businesses to drive more commerce and to reduce switching between other financial institutions for payment processing. These players are highly motivated to manage fee income erosion, and therefore, to the extent regulatory, geographic, and currency restrictions permit, expand their reach on the payment cycle through partnership and M&A accelerations.

- *Trends Influencing Global Payments*

Three high-level trends are shaping the global payments industry. First is globalization. We are living in a world of global commerce. Second, and closely related to globalization, is the digital economy and mobile commerce. Both have been a catalyst for the strength and increasing importance of global payment networks. The third trend is the overall increase in non-cash payments, both globally and domestically. It is not a stretch to imagine a world where commercial accounts and consumers specifically use debit, credit, and mobile-based services for all of their financial transactions. Specifically, these three trends are shaping the payments industry.

The global payments space is defined by large-dollar transactions, international payments, and the underlying payments business model of financial services organizations. The foundation of the sales side of our model is underpinned by the swift growth of accounts payable spending among the large-value commercial customers in global networks offering payment services. There are several assumptions related to the trends characterizing global payments and the analysis of firm performance within the global payments domain.

III. THE ROLE OF STRATEGIC FINANCIAL INTELLIGENCE

I argue that one reason many businesses do not succeed in effectively positioning themselves to take advantage of the myriad opportunities in the continually growing global economy is that they fail to gather relevant financial intelligence. Financial intelligence about current and potential business partners is relevant yet missing to a very large number of businesses. An unaddressed need is the capability to analyze financial data toward the end of learning important information about prospective businesses with which a firm may form a strategic relationship. Almost all firms need to be considering some form of strategic relationship to achieve sustained high performance. The questions are when and how. These are strategic questions, long-term questions, about the nature of the business, and its competitive position in the world's economy, which includes direct and indirect competitors, as well as possible collaborators. The capability to access, analyze, and act on financial intelligence addresses part of the how.

Given the direct relationship between economic engagement with foreign markets and economic prosperity, it seems likely that the potential for policy risk may keep potential partners from considering strategic relationships. However, the strategic opportunity is present more often for the partner that is financially more powerful. How to create opportunities and manage strategic financial relationships is a strategic question. The questions are difficult and require consideration of the potential partner's financial status. This capability is strategic financial intelligence. Strategic financial intelligence is the capacity to evaluate a potential partner's or competitor's financial status and how such information can be used to create or avoid strategic opportunities, even to identify the potential mixed motive variable that may be useful as well as the probability of policy changes concerning the financial question.

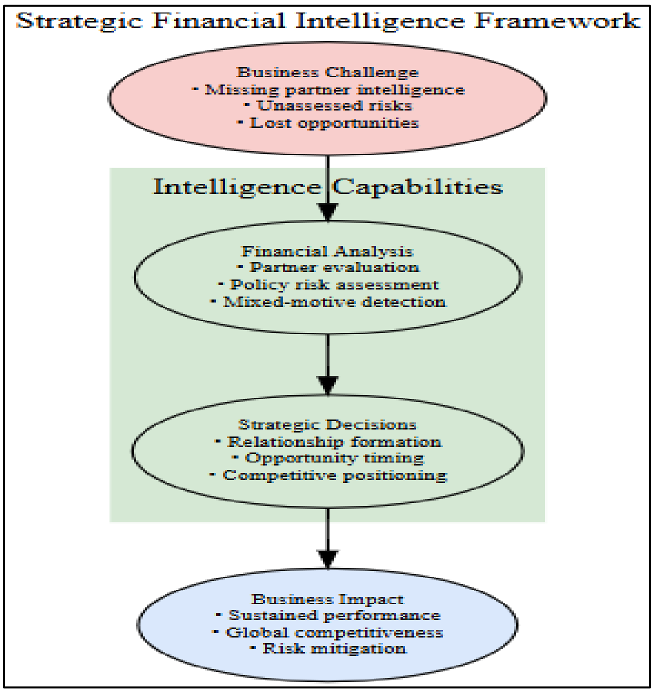

Fig 2 Strategic Financial Intelligence Framework

➢ *Defining Strategic Financial Intelligence*

Strategic Financial Intelligence (SFI) allows firms to leverage data analyses and financial expertise to make better strategic and tactical decisions. SFI provides for improved decision-making not only within the traditional financial domains but also helps firms optimize for leadership in key competencies and strategic imperatives. Such insights are typically reserved for the largest financial institutions. For such specialized functions, senior management sets and communicates the business and financial strategies to employees, shareholders, and stakeholders in annual reports, press releases, annual meetings, and other communications. This paper will detail how financial data can be used to inform the decision-making processes associated with strategic network partnership choices, but such analytical methodologies are just one part of the broader capabilities that define SFI.

Three main pillars support SFI: strategy, SFI capabilities, and effective partnership choices. The first pillar, strategy, encapsulates the business competencies operating to provide the business model and value creation strategies. Financial intelligence helps inform leadership as they set pricing strategies, geographical juxtaposition strategies, regional leadership strategies, etc. Through analyzing financial data, firms can gain a client-centric analytical perspective, which can help inform the strategy of a company through a better understanding of several financial implications created by partner choices. This financial data, when combined with institutional knowledge, forms the second pillar, SFI capabilities, enabling firms to optimize a company's financial position and maintain it over time. The third pillar helps firms make effective partner choices supporting the value proposition offered to clients. As is evident, the three pillars are not mutually exclusive, but instead complement and build on each other. SFI departments are therefore also uniquely placed in a firm and in their executive conversations to not only have a seat at the strategy table but also to help drive strategic business decisions.

➢ *Importance in Business Strategy*

A matrix can be formed where companies are classified according to their performance on two dimensions: financial performance and price-to-book ratio. This classification is important because the performance metrics will be evaluated on this classification. Under these topics, the paper develops four perspectives for the companies and states which models fit best to which perspective. The ownership structure and financial information for the data are defined. Furthermore, how to find the financial intelligence candidates and the implications of the performance of the designed models are given in detail. Finally, the paper concludes with the findings and limitations.

The strategy lies at the heart of the business, and creating organizational intelligence has a substantial contribution to making superior decisions in almost every company's department. It also plays a vital role in developing capabilities, leveraging competitive advantages, and finally the sustainable success of the organization. Measuring firm performance is significant in evaluating the success of a company's operating activities within the scope of its strategy. The measures usually involve financial and non-financial criteria. Over the years, depending on the change in the circumstances in the global environment, the importance of ending up fast in decision-making processes not only for the evaluation of firm performance but also to improve strategy has increased more than ever. The increasing competition conditions and the fact that investors attach importance to corporate governance practices and high corporate governance indexes have begun to take more place in the investors' meetings with firms. However, the ownership structure of the firms plays a significant role in the implementation of these governance applications. The leverage effect of corporate governance increases the risks associated with these firms and facilitates external financing, thus contributing to the business risk. Consequently, the financial indicators and the corporate governance indexes play a significant role in the comparison of such firms.

- *Applications in Financial Decision-Making*

We apply machine learning to enhance the global payments network value. Network effects cause global payment networks to increase in value for users as more users join the network. Given membership once joined, how can networks secure competitive vitality? In this setting, financial growth engines differ from those in other competitive landscapes. Financial decision-makers assess customer relationship strategies, differing across network industries. While traditional linear modeling using observed demographic attributes is informative within homogeneous customer bases, bi-directional models originating from AI subfields are particularly informative for decision-makers operating among heterogeneous customer populations. We discuss the strategic framework for using AI for high-value customer relationship management. Then, we illustrate applications among network member firms and network vendors. Frequently, financial management sets the economic fees for business. Where evidence suggests a good financial argument for charging a higher, growth-inducing price, intelligent leverage conveys that logic to a capacity-to-pay audience.

- *Background and Strategic Financial Intelligence*

Payments networks that operate across large geographies serve hundreds of millions to billions of users. For many financial products, large payment volumes present a high-value commercial stream. Consider an entity in a competitive market that charges a price based on the number of its followers. In isolation, its followers might decide to buy from the provider. Numerous followers amount to a stream of small revenues that add to a significant commercially viable total. As a network, digital platform owners provide valuable services for seller members using a stream of small payments by members or buyers. Small payments aggregate to substantial value in a high-volume market. Other global business networks include carriers like airlines, package delivery companies, and firm networks. As more firms join a business network, everyone gets a little bit more value.

IV. MACHINE LEARNING IN FINANCIAL ANALYSIS

Supervised Learning. In stark contrast to more traditional statistical methods, machine learning is entirely descriptive. The goal is to develop empirical rules that accurately predict high-dimensional outcomes from far lower-dimensional inputs. The appeal of this approach is manifestly simple. We have a well-defined target - economic and/or financial variables that we know have intrinsic value - and the machine learning model figures out an appropriate mapping from input primitives to the targets. Trading using this output is, of course, a natural application, but human investors may just as easily benefit from the framework. The promise of this approach is as exciting as the challenges are formidable, so we will make an effort to introduce it carefully.

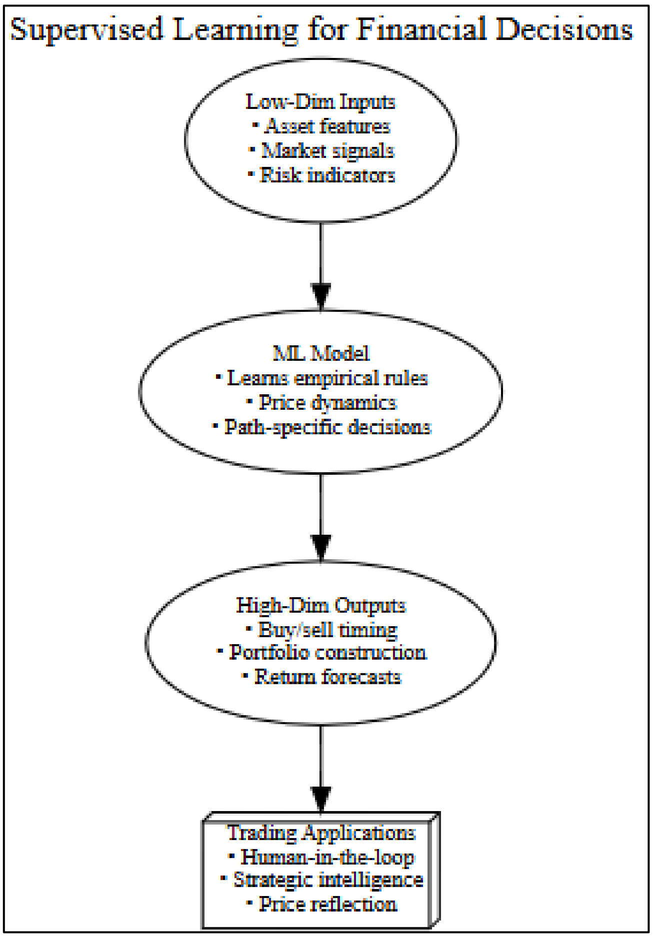

Fig 3 Supervised Learning for Financial Decisions

We focus on an important problem faced by real-world investors - when should one buy and/or what should one buy? - but we could just as easily be interested in selling and/or what we should sell. We can also be concerned with forecasting returns or constructing trading rules. The key insight captured here is that the value of investment selection is accelerated by real quantitative strategic financial intelligence. This term is used here to specifically differentiate between framing that emphasizes human values, aiming to serve perceived smooth utility dynamics, and a style of analysis that is driven by asset and liability signaling and risk appetites. Machine learning does not care about social norms or power-law attractiveness.

Similar to the approaches used by our ornithologist or astronomer, we take historical attributes and relate them to future properties of assets, strategies, or entire portfolios. This type of model is called supervised since we observe what decision a human would make as a function of some attributes so that we try to predict such decisions instead of the outcome. Such path specificity is essential because, in financial markets, assets are bought or sold, not held or passed over. Further, these purchase and sale decisions are characterized by entry and exit prices. Firms build business models around providing real-time guidance on the pricing of financial products. As we presently view the issue, we cannot even think about investment without thinking about price dynamics. Machine learning advocates that price perceptions should be informed by asset features and subject to reflection considerations.

➢ *Introduction to Machine Learning*

Financial institutions use the most advanced tools available in the industry to ensure the safety and soundness of their operations and make extensive investments in management information systems to collect and analyze large volumes of data. But information is also very important to help inform the strategic choices that their managers must make as leaders of complex organizations and networks. Business leaders must recognize that the information landscape has changed and that they must turn to more advanced, broad-gauged, and business-relevant tools to help them access and use strategic management information to drive organizational effectiveness and growth. The same financial institutions that will spend billions of dollars over the next decade deploying ubiquitous billion-transistor computers and connectivity to form the world's financial payments system are only beginning to understand the potentially strategic value of machine learning tools, algorithms, and insights.

Machine learning is a fundamental tool used in various computer science challenges today. Its body of work is substantial and addresses various questions in a principled manner. The goal of machine learning is to develop systems that can autonomously learn from data how to interpret, model, and predict in the aggregate the behavior of other information systems and related phenomena. Empirically, machine learning is about developing and using various computational algorithms to learn from data, where data are described by some set of features, a function or process embedded within the data is realized as the system output, and the algorithm concept or models this relationship. The domain of machine learning itself is not limited to a single type of mathematical or computational algorithm, applying regression, support vector machines, decision trees, decision rules, neural networks, and other methods. No single mathematical method is optimal, and a robust machine learning system will blend several of these tools to create an optimal set of system concepts given a specific learning problem.

➢ *Machine Learning Techniques for Financial Analysis*

In this subsection, we describe the machine learning methods relying on various linear and non-linear classifiers that we have used for building a financial news index. We have trained six different classifiers and have used the default settings for all of these classifiers. Training-related index information was then used in the final step to build information indices, which will be used in our empirical analysis. We have used a long sequence of returns $R(t, t + \tau)$ for τ h-period ahead returns, where $R(t, t + \tau) = 100 \times \log(p(t + \tau)/p(t))$ to capture the compound growth effect.

The classifiers used to estimate indices are as follows: Bernoulli Naive Bayes, Decision Trees, Random Forest, Gradient Boosting, Support Vector Machine, and Multi-Layer Perceptron. We use the package to fit these models. We also model these classifiers across 34 unique periods and pick the classifier based on the cross-sectional validation. Approximately four years of training data that spans all market disturbances should be used to find the best classifiers with lag effect for volatility measures, as they need to exploit the short-term profit-taking.

Equation 2 : Transaction Risk Scoring with Machine Learning

$$S_{\text{risk}} = \frac{\sum_{i=1}^{n} W_i X_i}{\sum_{i=1}^{n} W_i}$$

S_{risk} = Weighted transaction risk score,

W_i = Feature weight assigned by AI model,

X_i = Risk parameter value.

➢ *Case Studies of Machine Learning Applications*

This paper provides a new perspective and framework for how to use machine learning to improve financial intelligence, including a comprehensive treatment of desirable strategic properties of such computational methods. The results motivate specific uses of machine learning to enable improved payment system services for the real economy, particularly for network companies. The need for strong positive partnerships between good research and superior managers is underscored. Case studies of the use of machine learning within working payment networks underscore the potential and importance of these methods to strengthen the real economy, as opposed to primarily financial industry intermediation positive network effects.

Here we provide a number of cases based on actual machine learning applications, their rigorous testing, and the performance of these applications in working payment networks and payment processing companies. We chose to emphasize applications that can inform new and superior partnership-oriented payment processing services with the real economy, especially network companies. Before detailing the applications, some results from cooperation between the authors and three important companies provide context.

V. PARTNERSHIP-DRIVEN GROWTH STRATEGIES

The global network of payment platforms grows stronger with each additional partnership that is established to ensure a ubiquitous consumer and merchant connection. This chapter's empirical study has used collective insights to demonstrate a variety of strategies to inform partnership-based growth in the global payment network. Each of the unique strategies was learned by applying powerful tools that enable the practitioners to answer specific questions using their data: a single-pass machine learning algorithm was found to be successful at automatically extracting the intelligence from large-scale, hypergraph-structured transactions to accelerate the exploration of opportunities for targeted geographical growth encountered in a payment problem.

Through the use of fast greedy and hierarchical clustering algorithms in recommendations that enable the discovery and identification of similar platforms, we provide an example of the actual partner selection process that is used in the unique strategic business model of a global payment network. We provide the details of each of these strategies that can be achieved, all by leveraging panel transaction data from payment utility platforms. The sponsors of this chapter are regular participants in global and regional events that are focused on both financial and payment crime. The platform sponsors are also within, or have access to, a network of correspondent banks, incorporated entities, agents, and non-bank entities – such as payment service providers, logistic companies, and others.

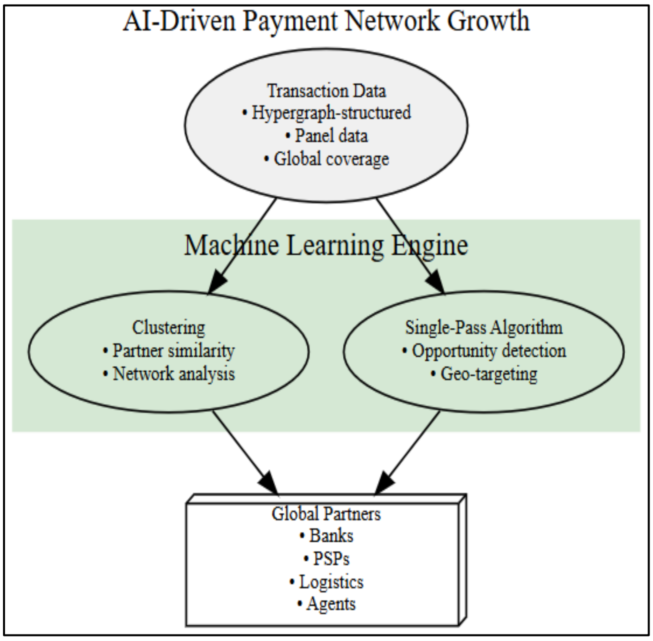

Fig 4 AI-Driven Payment Network Growth

➢ *Identifying Strategic Partnerships*

In the previous section, we identified a trade-off when setting up partnerships that can lead the payment network industry to be characterized by a suboptimal level of interconnectedness. In this section, we extend these ideas and argue that the potential growth opportunity associated with the respective strategies of different companies should play a role in identifying appropriate partnerships for a given company. In the case of a payments company, two important strategies are an attractive and/or increasing merchant base and technological expertise in building secure and user-friendly electronic platforms, either for the point of sale or for online environments. By explicitly including forecasts of sectors expected to grow in the future in the model outlined in the previous section, and examining the value of meeting projected demand, we demonstrate how a company can recognize the need to build strategic partnerships.

The results suggest that merchants seeking to implement in-store electronic payment systems should be suspicious if acquirers are somewhat reluctant to sign partnerships with companies that possess crucial expertise concerning the security and technical functioning of contactless payments. When using the tools that we develop to identify appropriate partners with useful expertise, such as advanced machine learning to deliver a better in-store experience, merchants should ask themselves whether the partners are appropriately recognized within the industry as potentially associated with important innovative technological abilities.

➢ *Evaluating Partnership Opportunities*

In our working dataset, UnionPay recently created new partnerships with several technological companies familiar to the US venture capital industry. Specifically, UnionPay established strategic partnerships with high-performing companies that strengthened UnionPay's HK merchant portfolio. Before announcing the partnership, these technological companies started to rapidly increase customer acquisition efforts. We discovered that 62% of the subsequently accelerated merchandise companies are funded by a top-10 VC, and 41% within the top-5. This share is increasing with company development stages: 30% of the applied companies, 50% of the failed companies, and 78% of the disappeared companies. Strategic exclusivity and position in anticipatory supply chain management and transaction lifecycle qualification are the underlying reasons for this phenomenon.

Furthermore, higher-ranked VCs and more funds seem to alleviate the conditional model COVAR. Given a UnionPay partnership, these qualified and funded rapid merchant members also show more competitive functionalities. (1) They usually cultivate merchant partners' competitive features in special industries. (2) They might recruit small businesses to expand the HK merchant pool and central cities using co-marketing or social marketing incentives. (3) They usually provide the most comprehensive services via broad technical connectors.

➢ *Leveraging Data for Partnership Decisions*

Using machine learning can be an effective way to use internal data to make informed predictions about partnerships. A machine-learned model to predict a strategic outcome symbolizes the lower bounds of information needed to justify the decision to pursue that outcome. It suggests the minimal information one would need to argue in favor of a partnership, a relevant list of partnership companies, or whether to pass for now and wait for more information. The defining characteristics of affirmative outcomes in partnerships with global payment networks are presented.

The data used to train the models are company and product attributes of each potential partner. Company and product data were collected through vendor and credit bureau data on partnerships and their close proxy public social communications. Given the non-negligible costs of vendor data and proprietary partnership information to validate data quality, it was estimated that one approach to identifying a club of payment network partners is significant enough to also train a partnership model using public firm information. The subset of information about private partner companies that are likely to exhibit the same defining characteristics that are most observable in public companies enables a greater number of companies to be included in the partnership evaluation model. Many of the same company and product attributes were used to train the supervised machine learning model, yet only a few are directly from the leading proprietary credit bureau data that contains all the privately held companies of interest.

Striking a balance with privacy, regulatory, and cost considerations allows a fairer arena for non-partner payment companies, including many who are vulnerable or first-time startups with fewer resources relative to established partnerships or other larger, industry-dominant networks to help keep the payment ecosystem safe and secure. By lessening network lock-in, the kind of machine-learned prediction model reduces the attractiveness of closed distribution, enabling new business models that do not require proprietary issuer or acquirer relationships. The model can be used to help potential partners see in themselves what a global network discerns.

VI. INTEGRATING MACHINE LEARNING WITH PARTNERSHIP STRATEGIES

In this paper, we aim to advance the knowledge of global payment partnerships by exploring the use of machine learning in gauging partnership development. We focus our efforts not without reason. Much of the global economy relies on the safe, secure, and efficient movement of money through very large value, multi-currency, and real-time payments. Organizations with global footprints make a myriad of payments every day, have credit or debit transactions with commercial or payroll, and need foreign exchange and cash settlements. These commercial entities demand 24/7, low-cost, high-volume, highly interconnected global payments. To satisfy this demand, banks build partnerships with strategic financial intermediaries in a set of economies. Banks exchange trillions of dollars in payments every day. The global payment infrastructure is ever-changing. The financial infrastructure reports elaborate on the growth in payments, the trend in system outages, the riskless value, aggregate transactions, and new developments. Many in the trade recognize good ideas and send a private thank you for the keen observation, but without stated empirical numbers that would justify an institutional implementation.

What a shame. Today, there are plenty of alternative data sources available that one can exploit to enhance the empirical work that guides future efforts. Access to messages by non-financial institutions, membership in relevant organizations, and choosing among a new generation of application processing interfaces permit interested researchers to gather the type of data that is needed to build the next generation of empirical models. In this paper, we plan to shed light on the predictions from a certain body of economic models. Economists who read the text will find a very familiar connection between the center and the things that the financial infrastructure models are concerned with. The project, however, focuses on proving predictions, not the foundations for those predictions. A financial institution is defined as "an organization that operates at the center of the financial ecosystem, enabling its customers to send and receive money easily and safely. Any financial institution in the world can connect with financial institutions and the accounts in the network."

- *Data Sources and Integration*

Although extensive historical financial transaction data exists, data availability is a critical restriction in payments network research as none of the core commercial database vendors sell money transfer data nor can they describe who remits or receives it. We overcame obstacles together: and provided data to collaborate. The global cross-border user-end analysis is based on data obtained from which is derived from the flow data and reports generated from branded locations. Using the WFE and co-located units, this data origin includes licensed entities in various countries. We direct clean, validated data of all remittance locations and financial transfers that were processed by the Principal or its co-located units of a financial unit with a similar parent in a location along with identification data. The data does not contain customer information, so transmissions or connections cannot be assessed along the wire. Additionally, the data neither differentiates whether the individual initiating a transaction pays a fee for their use, presents another asking for withdrawal, or the instant asking to be paid at sight. Of note, no proprietary and/or personal user data ever leaves the firewalled sites. It is important to highlight, however, that the partnerships held with other companies depend upon it managing fundamental customer and proprietary data.

- *Predictive Analytics for Partnership Success*

Partnerships are a major source of growth in the crowdfunded global payment industry. When consumers want to send flowers from the UK to a recipient in Mumbai, when a business wants to pay their remote software developers in Kazakhstan, and when a shopper on the beach in New York wants to pay a street vendor in Greece, they expect to use a global payment network to help perform the currency exchange and settlement. These are some examples of the international payments made by businesses and consumers using the global networks of payment partners.

The key to designing successful international partnerships is hidden in the data about consumer and business demand for the usage of those networks. I collaborated with the team to use machine learning techniques to analyze the demand for end-users international payments. We examined the performance of our current partner network and used an analysis of internal and public data to propose additions to the partnership network. The analysis adds value to the supply and demand drivers for the company's existing friendship and partnership alliance strategies and uses predictive tools on a globally weighted competitive playing field. After implementing the proposed solution, the machine learning model demonstrated accuracies of 73.5% for predicting that a country-to-country connection will have demand in the first year after adding the partner.

➢ *Challenges in Implementation*

This strategic framework requires very careful management of big data and machine learning. The enormous potential available from a big data-machine learning problem should be balanced against the very high resource requirements, particularly talent, organizational, risk, and ethical considerations. We are effectively claiming that what is infeasible becomes feasible with a very high-risk project. This should be done with considerable care. The training of data scientists capable of non-trivial feature selection in new data environments and capable of maintaining the highly complex neural networks required for this task is likely to require a lengthy and successful research and development process. The use of such a striking breakthrough also has substantial secondary absorptive capacity requirements. Senior managers must be able to ask difficult questions, and primary users must know how to interpret the results to prove the enormous potential of business intelligence. In addition, the entire system remains endogenous, and the model is only as reliable as the data with which it is trained. More traditional approaches to financial intelligence are also required, as a great deal of informative data is proprietary. Most machine learning techniques also require a massive amount of computation that is not always readily available or presents implementation problems. In addition, connecting multichannel data, particularly if it is proprietary, will frequently present legal and ethical problems. Consequently, any project thesis is at substantial risk of failure. It is not immediately intuitive or researchable which machines learn especially well. Moreover, if they are proven able to learn, it is difficult to determine what features they identify that determine the functioning of the world. Finally, we should also be cognizant of the problems highlighted by ghost-in-the-machine learning, or the inherent difficulty of explaining exactly how a machine arrived at its conclusion.

VII. CASE STUDIES OF SUCCESSFUL IMPLEMENTATIONS

We now apply our proposed solution using machine learning to two very different questions, both involving the design of network-based strategies to stabilize financial networks faced sharply with exogenous change. The first case is typical of a geographic shift from 'correspondent banking' to the use of central bank settlement. The second case involves how to execute merchant acquisition in the Ghana interbank market. The solutions, based on a very small dataset assembled to test the methods with known and simple results, demonstrate the existence of robust computation and machine learning to develop strategic financial intelligence. This section is empirical. These cases are based on traditional small data in-house analyses concerning the recent past and immediate future data related to correspondent banking and banking reform. The data section provides a short description of each set and the financial and payment network organizations operating them. Section 8 develops the framework and presents the optimization problem. The resulting cases are simple due to the special properties of the solution.

➢ *Global Payment Company A*

We employed a machine learning process to produce strategic financial intelligence (SFI) that informed the expansion of one of the world's largest B2B cross-border networks. Since the network experienced 17 years of managed economic cycles between 50% and 150% growth, a comprehensive business strategy informed by good financial analysis was needed to guide strategic partnerships sustaining the network's ongoing rate of growth amidst the credit crisis-induced global recession that occurred during the project. We utilized three main algorithms to carry out this research: the regression algorithm to support profitability scoring clustering; the classification and discounted cash flow abstraction algorithms for growth scoring clustering; and feature importance scoring.

Payment processing and cross-border settlement services are provided to many businesses and governments around the world by a systemically important company that has been operational for many years and has both physical and virtual components. Approximately 2.5 million partner locations in 200 countries send and receive transactions through this company. While it processes a large number of relatively low-value transactions to and from many different sources for a fee, the actual transfer of value occurs either through a proprietary settlement network or partnerships with other financial institutions.

➢ *FinTech Startup B*

Brought to bear, deep learning can be expected to find highly non-linear structures in complex financial optimization landscapes, yielding transformational fintech advances. Our team, from inside leading financial institutions, has designed the capital base and investment strategy to put into practice these groundbreaking techniques. Our approach natively accounts for hyper-aggressive negotiated interchange fee caps without tampering with sophisticated nonconvex algorithms, scalable up to time complexity in the number of agents and payment volumes. Payments leverage tradition as one of humanity's most ancient laws, a source of enduring evolutionary advantage. Our thoughtful barrier to entry in payments as a call center balanced boost insulates from significant possible cash flow impediment influence from regulatory turbulence.

As the co-founder of a company, and by focusing on the competitive advantage of quality customer payment transaction data alone allowing solid differentiation in basis point level customer lifetime value calculations, I've built a pre-seed funded company concentrating on strategic financial intelligence using machine learning and deep learning. The mission is the formation of expert global payment networks by the propagation of best fiduciary practices. The future of machine learning fintech for payments holds both niche and boutique. Boutique investment in the company, parallel to its seed grant, positions and protects the proposed direction of travel in the strategic partnership due to tech stack integration with obfuscation-resistant secure transmission payment industry giants. We have successfully engaged all three regulated payment logos and are being courted by many others.

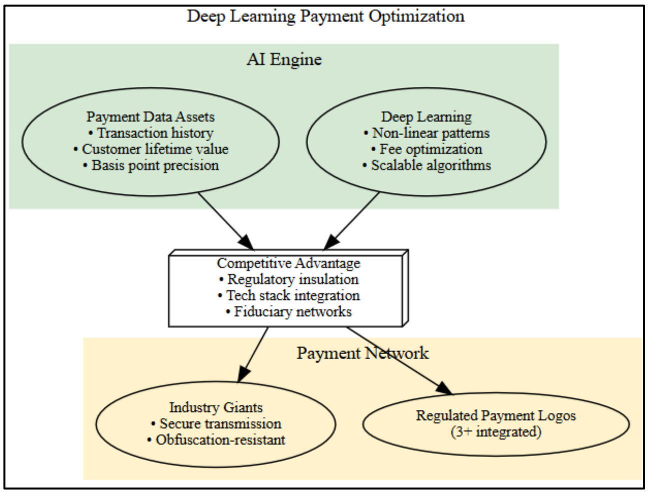

Fig 5 Deep Learning Payment Optimization

➢ *Traditional Bank C*

Despite technological innovations in the non-bank remittance services sector, traditional banks may still be in a position to exploit their natural advantage for cross-border transfers when they cooperate using a network scheme strategy. Now that the cost of electronic and mobile transactions between customers is low, technology itself is of less use as a strategy for a standalone new entrant. It is only financial institutions with an easily accessible large number of agent locations in rural areas in source countries that are likely to be able to exploit the network externality advantages of a global money transfer network. Currently, traditional banks can process cross-border transfers from other banks in real-time at a low cost because they maintain nostro and vostro accounts with sufficient balances in various countries. In other words, they are the only financial institutions that already have reciprocal agreements with many other banks in the world, eliminating the need for customers to pre-fund accounts. This situation is different from the story of plain vanilla customer-to-customer transfers, where the existing network of financial institutions can be a high-cost impediment to the provision of remittance services. The key advantage that banks have is that they can make full use of their existing infrastructure and, secondly, they can share high costs through cross-border transfer pricing with other customer banks recalling these bank partnerships. At the same time, they diversify the risk across a broad customer base. The concept of a financial institution sourcing funds cheaply for payments is as old as banking itself and is often supplemented by the concept of a bank handling transactions on behalf of its customers directly with each other.

VIII. REGULATORY CONSIDERATIONS

Using machine learning algorithms can help inform growth strategies while positioning for change also requires the integration of regulatory intelligence and a strategy based on a deep understanding of why model outputs give selected results. Jurisdictional considerations include anti-money laundering/combating the financing of terrorism and customer due diligence, as not every machine learning logic will be applicable in every region or for every legal entity. Understanding the global payment requirements and client needs will also help streamline data integration and AI influence throughout the model training and parameter-setting process, from the beginning with the end in mind. Staying close to the industry and monitoring the environment will help inform changes within the model. While it ultimately is up to the financial institution to risk rate and onboard a customer base, stronger, more defensible model outputs can help in explainability. Approximately 92% of the incidents or queries arise from 1% of the clients, which implies a client base approaching 34,000 global banks form less than one-tenth of 1% of the issued queries. Smart engagement with AML/CFT logic and jurisdictional data integration represents a core value proposition.

Specifically, within the framework, three considerations are proposed: visibility, transparency, and integrity. The strategy is designed to address the tensions and problem sources of AI bias, while machine learning represents a novel approach to utilizing and synthesizing a substantial and complex data series. The application of financial intelligence is focused on the establishment, success, and smart growth of a Client Data Integrity Utility proof of concept that is designed to be integrated as a module within a customer due diligence system benefiting both existing global financial infrastructure collaboration and new dynamic and elastic financial systems currently under development.

➢ *Global Regulatory Landscape*

Today's global financial community has long since established strong transborder operating standards for the discharge of diligence and due care in the conduct of its cross-border transactions. Beyond that generalized level, however, lies a variety of critical global interest issues that relate to dealing with private foreign entities, citizens, and institutions; identifying, for purposes of appreciating the geopolitics of distinct regional or country affairs, making necessary personal contact on known material circumstances; and achieving a position of being able to know the identity, legitimacy, probity, and status of the foreign principals.

To accommodate the specific interests of the United States as well as several other developed countries, an increasingly larger and more detailed network of supranational supporting structures has been traveling along several different but compatible avenues. This subject defines the topic of anti-money laundering and antiterrorist financing technology in the context of borderless financial products and service delivery channels. Even though the twenty-first regulatory test bed is the United States at the federal level, the EU and its many member jurisdictions have been moving ahead quite rapidly in strengthening their rules and standards. Despite differing U.S. and E.U. histories and cultural orientations, the various on-time U.S. and E.U. legislative tracks may in a reasonably proximate future lead to a common global due care due diligence standard for availability.

- *Compliance Challenges in Payment Networks*

The potential for money laundering is asset-based: institutions' assets. A financial institution is attractive for money launderers if it has a resilient asset cushion, meaning that there is a sufficient amount of assets available and that those assets will not quickly deteriorate in value if something goes wrong. Institutions can be made unattractive by imposing controls or by creating illusory asset characteristics that trick potential money launderers.

Payments can be early warning indicators of risks such as money laundering, fraud, credit, and settlement. However, individual networking participating firms do not share enough of the relevant business characteristics for payments to be used in aggregate. To use distributed payment networks to help manage enterprise-wide risks, the network must be provided with a synopsis of policies, reputations, business models, and objectives of each participating entity. This section describes the challenges widespread participation raises for a distributed global payment network and the consequences that impairment may have on motives for settlement system migration.

- *Impact of Regulations on Machine Learning*

Given the potential data breach issues that may arise with an algorithm focused on large-scale use of data, it becomes much harder to extract data from multiple sources intelligently in domains that are sensitive to privacy breaches without infringing on regulations or breaking laws in other countries or cross-state regulations. While this is a reasonable legal framework — data protection and individual privacy are fundamental civil liberties — most firms also must trade off the loss of intelligence that results from retaining data within the organization, due to the potential negative financial consequences to the company. This isn't just data court orders that exist but also legal restrictions that prevent banks from selling some information that they are legally restricted from releasing to outsiders. However financial innovations can occur, and a recent approval could lead to data containment that allows businesses to improve financial intelligence models.

IX. FUTURE TRENDS IN PAYMENT NETWORKS

Global growth in the use of electronic financial services has provided significant incentives for financial technology start-ups to both compete with established financial players and partner with them. At the same time, officials from around the globe have sought to modernize and strengthen the safety and soundness of their respective financial systems and have called on financial regulators and supervisors to adopt new regulatory frameworks to address regulatory gaps, respond to potential risks arising from new financial technologies, and ensure the ongoing resilience and interoperability of a rapidly growing and evolving global payment network. Their focus has included ensuring that the safety and soundness of new and existing financial players better align with the ongoing strategic, financial, and related purposes of the global payment network, which encompass the flexible leverage and disciplined management of liquidity, credit, and other risks associated with a variety of payment channels. Existing financial players are the largest and most systematically important participants in the global payment network. Mission-driven, private sector partners are also working with key financial regulators to modernize and expand this network and can leverage specific payment capabilities that have been or are being developed and implemented by other leading fintechs. Policymakers from across the globe at both the multilateral and national levels, particularly in emerging and frontier market economies, have embraced the promise and innovation related to a wide range of modern electronic financial services. The successful delivery of these services can streamline the flow of funds, promote inclusive growth, and strengthen the reach of businesses and communities, improving economic development and resiliency. Given the magnitude of the ongoing financial and economic innovation, many of these policymakers have also called for these new payment capabilities to be delivered safely and efficiently, using globally consistent technical standards and best practices. However, for several reasons, including the cost-effectiveness of partnerships, many existing players are not able to meet these calls on their own.

- *Emerging Technologies*

Current conditions are ripe for innovation with emerging technologies.

When Mastercard was founded in 1966, the world was a very different place. Monetary exchange, the original Internet of commerce, was primarily conducted in cash and checks. Over the past 50 years, the shift to more convenient electronic forms has fundamentally changed the nature of global commerce. But during this half-century, innovation for the modern world of convenience has been more strongly based on leveraging existing technology, including electronic computers, software, and the internet, to add value. We now operate in a time when truly foundational disruption of many industries is feasible as a result of rapidly growing fields of new technology such as machine intelligence, genomics, material science, energy solutions, and others. This ready availability of deeply meaningful new tools has shaped how in-house development at Mastercard is oriented around maturing a sizable portfolio of vexing business problems that emerge from the technological future—problems where effort today has clear pathways to economic advantage tomorrow while resolving critical unmet needs of our business partners in the meantime.

Enormous initial value has been generated in areas including search, e-commerce, and social media. Some well-tread areas have included financial services, where most early attention was related to direct operations in capital markets for algorithmic trading and risk management for predictive portfolio positioning and potential capital requirements—their primary purposes in both cases. And of course, the power of machine intelligence is well substantiated and applied in customer-facing environments from personal interactions to commerce, including capital investments, and it has shown tremendous potential in the health sciences. Business-facing applications, however, are relatively underrepresented across many key industries, financial services included—but no longer at much larger, partner-centered entities such as Mastercard, which link into a global network of buyers and sellers where meaningful and challenging problems abound with shared financial success. Through numerous examples, this discussion demonstrates the evolving concept of strategic financial intelligence at work in the context of partnership-driven global payment methods. The underlying mathematics of implementing strategic financial intelligence are described, as questions of why and when efforts such as these are best undertaken. Note that the applications are strategic—meant to provide significant revenue to either business owners or investors. They serve a customer-facing environment by creating new data by monitoring precarious statutes as they evolve socioeconomic trends.

- *The Role of AI in Payments*

The global vision of a wide range of partnership innovations includes new product collaborations, partnerships between banks and leading technology companies, and leading regional brands during the building phase. It also encompasses bank sector strategies to create innovation platforms that facilitate technology and process development and improve the skill set of employees in specialized sectors. There is a significant synergy that emerges when banks and technology companies work together. This ranges from an improved digital customer journey to the completion of long-term payments that support global trade.

The collective banking management body is aware of the potential impact of the major issues to be addressed and has identified the need for a global clearing system that eliminates the negative consequences of competition. Affordable access to day-to-day global financial interactions is a social necessity. Payments are a fundamental basis for the financial system. Advances in artificial intelligence have the potential to bring several strategic and operational benefits to payment service providers, such as key actors, technology companies, and banks, who must offer an innovative assessment framework to capture many of the potential benefits.

Equation 3 : Cost Savings from Machine Learning Optimization

$$C_{\text{save}} = C_{\text{manual}} - C_{\text{ML}}$$

C_{save} = Cost savings through ML,

C_{manual} = Cost of manual processing,

C_{ML} = Cost after ML optimization.

- *Global Economic Factors*

Understanding the resiliency of global economic factors Modeling the strategic financial intelligence of global payment networks at a target level with granular machine learning is a massive step forward, somewhat analogous to creating comprehensive maps that allow trucks to transport goods more effectively. While this work provides a sound observational framework, the utility of these findings extends only a level or two deep into the causative structure of these relationships. For example, while the cross-industry level connections may suggest that providing payment services for agriculture sectors is particularly important to a country's economy, we cannot express any clear deductions about the next, let alone the far-reaching influences of this relationship. The reaction of factors within global economies to shocks such as those resulting from the global financial crisis creates dislocation and news irrationality, providing fertile grounds for strategic investors who can continue to act in the long-term interests of a portfolio. Applying a broader financial intelligence perspective and principles, we next suggest a few anecdotal macroeconomic deductions to further inform geography hub strategy: the strategic importance of global export GDP, labor skills, and infrastructure within and among country geography hubs cannot be ignored, bearing in mind the critical trade finance origins of payment service demand. As a measure of hub resiliency, the ratio of risk capital and investments to total GDP points to the ability and willingness to invest in new economic capabilities and new industry formation, key elements in transforming a hub from an economically vulnerable importer to a locus of economic activity and growth, particularly in an increasingly digital world. Influences related to global payment network development also hint that geographical factors related to social modeling stand as first noted in the classic field's forefather. High levels of international exposure, as partially indicated by relative volumes of imports or exports, suggest business activity that can fit into or supercharge a network that already has a global presence. Resiliency in global GDP, inflation, interest rates, and foreign exchange rate estimates is important not just in isolation but also relative both to nearby country expat traffic areas as well as to other global economic factors. Balancing them can be interesting. For example, inflation and foreign exchange rates, or interest rates and GDP estimates tend to be negatively correlated. Considering these relationships, geography hubs can execute trading or hedging strategies that might provide some protection during periods of potential macroeconomic weakness. Indeed, they would be well served to analyze the empirical data in many of the modeling relationships noted here and to carry out strategic hedging for these data-derived insight risks as part of the repository financial intelligence process.

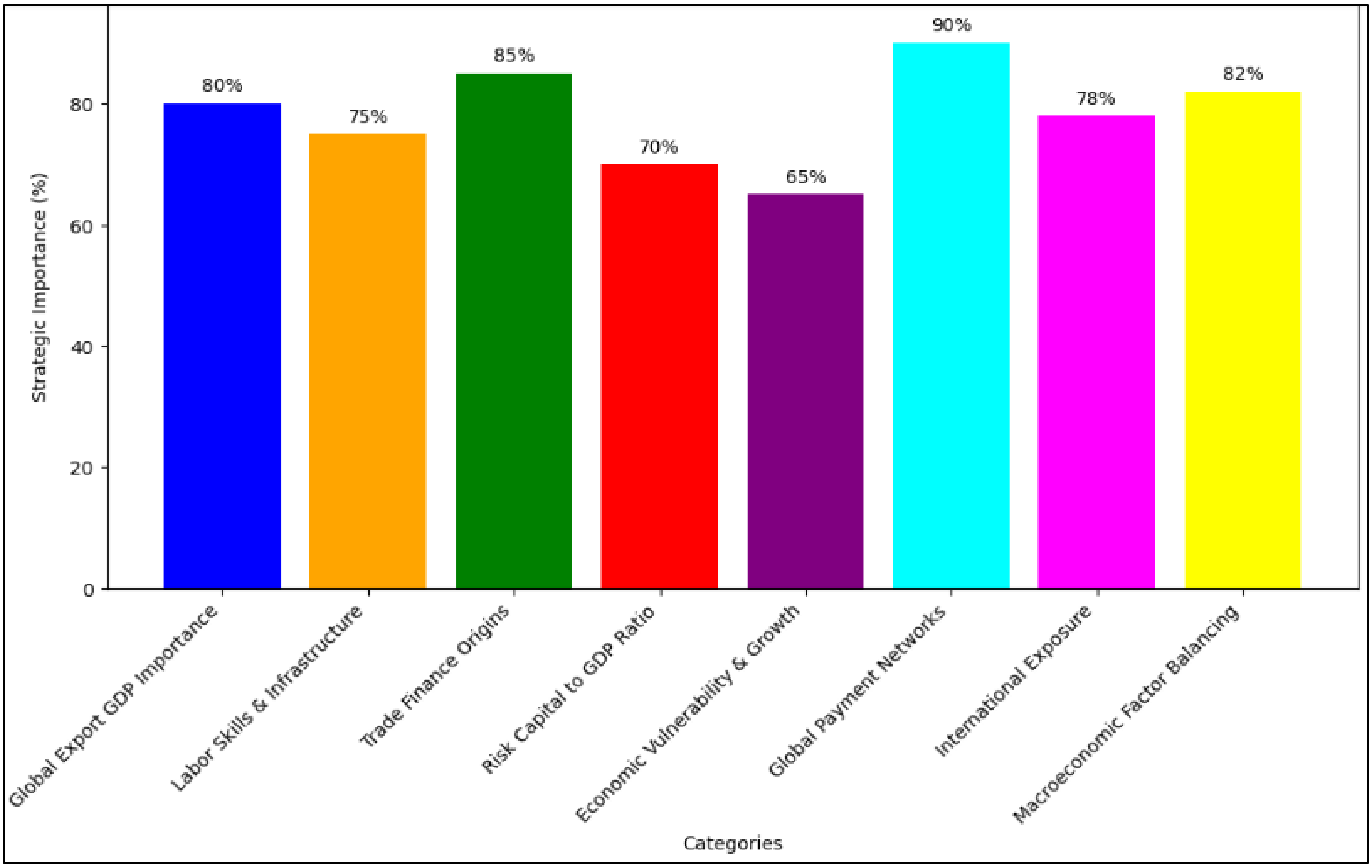

Fig 6 Resiliency of Global Economic Factors & Payment Networks

X. CONCLUSION

The over-the-top growth in multi-sided platforms and associated payment network business models has been well-documented. In some cases, their core payments funding, authorization, clearing, and settlement income are growing at quite exorbitant rates. The associated relative profitability is also leading to attempts by platform sponsors and communities to "over-locate" costs within their value networks. Consequently, as well as managing the complexity of multiple structures, it is no longer simply a case of balancing the reducible transactional frictional costs against the non-reducible value proposition. This is going to become more complex as the business models evolve from "own and organize" to "enable and facilitate" to "service and support". Adding to the intrinsic complexity are uncertainties over the degree of industry vertical consolidation and public/private market interface.

To deliver long-term value, ecosystem strategic intelligence needs to balance exuberance with longer-cycle empirically enhanced dialogue. The incorporation of systematic lessons from data manipulation, scientific triangulation, and machine learning should help API designers, payment gateways, platform sponsors and their marketplace partners optimize lasting shareholder and stakeholder win/win relationships. But this is only a foundation. To achieve a dynamic sustainable market value proposition and to trigger supportive network effects, it should then cascade that learning to ultimately motivate and support the interactions of consumers and producers. If we are not all in this together, we may all fail together.

➢ *Closing Reflections on Financial Innovation and Future Directions*

In this chapter, we entwined the discussion of the notions of financial innovation and strategic financial intelligence within a unifying element – the FinTech sector, and more specifically how machine learning techniques can be applied to the study of these two issues at a particularly critical juncture of payment networks, the interactions between the demand and supply sides of the business, shaped by the revenue-sharing partnerships that characterize the merchant acquirer-banking sector ecosystem. A key motivation for our research is that both the retail payments ecosystem and the payments R&D communities increasingly acknowledge that it is not easy for payment to launch ubiquitous payment platforms, relying on their network, technology, operational channels, and risk management capabilities. This functional specialization necessitates a revenue-sharing agreement between payment networks owned by acquirers and issuers, with the establishment of four-party networks that mutually meet the needs of different stakeholders. If financial innovation is about the design and introduction of new financial products, model organisms, and institutional designs, and if strategic financial intelligence is about the combination of sustainable strategic choices with dynamic capabilities that allow innovation to flourish, then we argue that very important, yet hitherto vastly underexplored opportunities lurk in how FinTech start-ups might use advanced machine learning techniques to very creatively inform these partnership-driven innovations in the global payment card space. These partner-versus-compete motives may indeed vary for different market partnerships. However, there is a familiar theme, which is that both FinTech and financial organizations strive to extract and maintain returns from digital financial services, underpinned by the consumption and production functionalities built into apps or products. These models enable changes in customer and merchant behavior. All partnering agreements result in new strategic directions that reduce entry barriers and facilitate the entry of non-banks and foreign financial institutions; these financial user experience platforms facilitate time and energy management. Banks must adapt their open innovation routines to learn from each other's strategic practices and from those of the tech start-ups that are reordering the competitive financial industry landscape.

In this chapter, we presented a strategic optimization approach to evaluate essential variables of business transaction decision-making in merchant partnerships; in so doing, we introduced a new empirical paradigm to financial service platform engagement. We present empirical work based on international debit card data and discuss the key challenges and opportunities faced by FinTech in making use of these interesting signals to establish or grow a presence in the lucrative merchant marketing or mobile payment technologies. Based on our data-driven results, we close with qualitative discussions and quantitative interpretations of how various machine learning models can be incorporated from the demand and supply sides of the partnership revenue-sharing contract to help answer important strategic questions of payment network revenue and growth. We argue that several applications in the usage of the developed intelligent agent can be partners belonging to the global merchant payment network. In a world where machine learning and business automation have far outstripped user desires, the agreement can be between profit-maximizing banks and information-disclosing FinTechs. Banks are mandated to produce and use more financial intelligence; brands are prohibited from making or increasing payments without changes in the consumer's contractual terms, whether binding or not. Banks, as data controllers, are aware of these revenue-sharing provisions and are responsible for the systematic production and policy application to provide for those exclusions.

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