Efficient Automation of Decision-making Processes in Financial Industry: Case Study and Generalised Model

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Abstract. Businesses become digital as emerging technologies invade economies. Cognitive technologies and artificial intelligence shape novel business models and decision-making processes, and customer experience. The technologies penetrate largely, and profoundly the financial industry switching to automated lending decision making replacing traditional financial service models and restructuring the markets. These developments intensify the discussion on business performances and efficiencies as results of the innovation implementation. In this context, we study the decision-making process impacted by information technologies and fintech achievements study and the method of organising a more efficient business process. Our research carries on a case study of innovative business management in fintech and the impact of automation of decision-making processes on the organisational business value. As a result of the research, we design a general business value framework to assess performances on input, processes and output stages, then we evaluate the efficiency of the artificial intelligence application within the studied financial institution, and we suggest additional improvements in efficiency assessment as well as next-stage enhancements and strategies founded on the latest fintech developments and trends to maintain high competitiveness. On its basis, we offer a generalised fintech AI application model for other similar companies that could be implemented widely and directly for efficiency analysis.

Keywords: Decision-making, Artificial intelligence, Efficiency, Digital economy, Digital transformation, fintech.

1 Introduction

Emerging technologies invade economies. The modern society becomes digital, and the businesses become digital. The ‘digital natives’ [1, 2] live intensively in networked digital technologies contexts. The ‘digital native organisations’ [2] step out from the traditional approaches to do business, to understand competitive environments, to solve problems and make decisions. This shift in mindsets and paradigms leads to agility performances of the companies that accelerate business results when exercising rapidly, focused and flexible.

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These new developments known as 'Fourth Industrial Revolution' [3] impose (i) novel business models, (ii) intensive use of information resources to improve products and services and increase productivity, (iii) different forms of partnerships for collaborative innovations, and (iv) priorities on customers' expectations and customer experience. Innovation-based competitive strategies boost companies' competitiveness rather than traditional cost competitive advantages. Higher competitiveness results in greater market share and management efficiencies are fundamental towards achieving above-average profitability within the industry [4]. The businesses are technology-empowered by recent and significant progress in fields of big data, data analytics, the computing power of machines, and cloud services that soar the artificial intelligence (AI) technology and its application.

The AI is rapidly changing how financial agents operate in fields of customer service and communication, risk management and other core functions in finance. The growth of global fintech investments across the main activities such as payments, insurance, planning, lending and crowdfunding, the blockchain, trading and investments, data and analytics, and security, is more than 18 times from 2005 to 2016 [8].

A broad palette of factors enhances the use and spread of AI technologies in the financial industry. Additional descriptions of the results of the application of new technologies, including AI, are given in the publications [5-9].

Still, there is little evidence on how the organisations measure the AI technology effects. As one of the leading industry applying AI decision-making automation, this problematic arises even strongly in the financial industry.

Thus, our subject of research is to study the method of organising a more efficient business process in a financial credit institution using AI technologies. Purposefully, we establish three interrelated tasks: (i) to explore the decision-making process and the improvements the information technologies and fintech achievements carry on it, (ii) to review the management approaches to assess performances and to develop a general business value framework for fintech credit institutions, (iii) to analyse a case study of innovative business management in financial industry, applying AI decision-making automation, and to examine its reach on business performances and efficiencies.

The research methodology implies a review of theoretical backgrounds in fields of management, decision-making, and efficiencies, and artificial intelligence, and an empirical study of fintech business use cases based on content analysis and structured and unstructured inquiries to management.

As results of the research, we expect two primary outcomes: (i) general business value model for efficiencies evaluation of AI decision-making automation in fintech credit institutions, and (ii) assessment of the efficiency of the novel business process in a financial credit institution using AI technologies. Finally, the general business value model and the novel business process are used to form and offer on its basis a generalised AI application scheme for other similar companies.

The present study is limited only to management aspects of AI application. So, we deliberately not focus on technological aspects nor mathematical or statistical apparatus behind machine learning and AI.

2 Human or Machine Decision Making

The data-driven decision making necessitates critical answers. As for the collection of data, it is about sources, depth, and details. What kind of technology, processes, privacy rules, location, security, architecture and governance, and displays to prioritise for information storage, management, and access? Also, the useful information "meets the test" of five criteria: (i) timely (available when needed), (ii) high quality (accurate, reliable and used with confidence), (iii) complete (sufficient and up-to-date), (iv) relevant (appropriate) and (v) understandable (clear and easily understood, presented in dashboards or scorecards in real time) [10, p. 132]. With the application of modern AI tools, data-driven decisions become fully machine-equipped. Not only the first stages of gathering and storing information are computerised but so are the next ones of analysing, predicting and deciding.

Organisations are using AI technologies to extend the knowledge base, respectively the power of the middle management or expert personnel. The expert systems perform in the specific and limited domain of human expertise based on the implemented set of rules. They are useful to solve problems that are "*difficult enough to require human expertise for their solution*", acting as "*model of the expertise of the best practitioners in the field*" [11, p. 26] using both common facts and sources of data and heuristic knowledge ('rules of thumbs').

In addition to that, it is appropriate to state the distinction in decision making due to the type of problems to be solved. Routine, usual situations and repetitive decisions are to be handled by a standardisation approach. Those so-called 'structured problems' can be dealt with 'programmed decisions' based on experience, established business rules and procedures, identified factors of influence.

Also, humans do not always act rationally in complex situations of information asymmetry, such as credit lending [12]. Credit inspectors are driven by (i) own motives that affect lending decision making such as mood, overconfidence, and career concerns, and (ii) some personal traits of borrowers (beauty, race, and age), (iii) flat-based compensations with incentives for loan approval encourage higher credit rating assessments, (iv) desire to reach own goals by means of manipulation of soft and hard information. Often credit inspectors make decisions from a limited dataset (credit ratings) and limited reliability of creditworthiness calculations. It is unusually bold for specific segments of the markets such as non-residents and unbanked or underbanked customers. Borrowers also behave in their benefits to obtain credit and lower interest rates influencing the appraisal process and misreporting financial status.

Quite obvious is that when the decision-making is not accurate for some reason, the default costs increase. More, it engenders missed revenue due to rejections of creditworthy customers. However, some evidence introducing credit-scoring technology drives to fewer incentive problems, focus on difficult-to-evaluate loan applications, decrease of default probability of loans and increase in loan profitability.

In the cases described, AI technologies can have a significant positive effect, reducing the apparent and implicit losses of enterprises.

3 Impacts on Business Performances and Efficiencies

According to economic theory and the rationality-driven decision-making, the available resources are used optimally to achieve the planned or expected organisational objectives and results, which imposes the relevant analysis and decisions on the organisational structure and behaviour (value chain performance approach), the resources and competencies, pursuing to eliminate the '*X-inefficiencies*' [13, 14] depending mainly on the management.

Still, there are ambiguous findings in management theory on how to assess effectiveness. Different approaches such as the goal approach, the resource-based approach and the internal process approach integrate into the 'contingency effectiveness model' [15]. A popular approach to measuring organisational effectiveness is the stakeholder approach, reflecting the interests of different stakeholders such as founders, customers, creditors, personnel, suppliers, society, and government. The palette of criteria, in this case, comprehends income, creditworthiness, and quality of products and services, contributions to society, satisfaction and salaries, managing style, regulations compliance. Both objective and subjective (quantitative and qualitative) indicators find worthy places in management approaches to assess effectiveness. However, choices depend on businesses and industries, and management styles.

Despite the fact that each organisation has its own individual characteristics, organisations have universal general benefits from technology-driven leadership such as establishment of (i) knowledge base (no dependence of staff leaving), (ii) mechanism avoiding human emotional instability, (iii) eliminatory of routine and unsatisfying jobs, (iv) enhances of organization's knowledge base by generating solutions to specific problems, too massive and complex for analysis by human being in a short period of time [6].

Laudon & Laudon [6] group the business value in three groups: (i) common costs, (ii) tangible benefits, and (iii) intangible benefits. Tidd & Bessant [16] propose a framework to measuring innovation performances familiar to standard system approach that implies: (i) the inputs to innovation processes, (ii) the innovation processes themselves, and (iii) the outputs measured by per cent of sales, profits derived from them, customer satisfaction surveys. The strategic impact of the innovations on the overall business performance is another track to being taken into consideration indicated by the growth in revenue or market share, improved profitability, higher value-added and other more specific indicators. Both financial (ROI, operating margin/EBIT/EBIAT, unit costs) and non-financial performances could be measured using the management tool of the balanced scorecard [17].

Gružauskas & Statnickė [18] argue that AI enables the businesses to increase productivity and profitability dramatically, having the benefits of AI application expand beyond cost-optimisation to fewer environment effects, decreased lead time, increased utilisation, higher variety of supply. AI has effects on cost savings and operational efficiencies. There is substantial value achieved by taking advantage of AI to pursue new competitive strategies across the chain value [19]. Apart from the lower default rates, it leads to business outcomes optimisation through better insights when integrating a large volume of data; increase the efficiency and scale of retail lending.

Advanced credit decision models based on AI can improve the confidence of lenders to extend credit. Also, the alternative data sources can be used to assess creditworthiness in segments for which data is not readily available.

Consequently, based on the theoretical review and presented considerations, we have developed and offer the general business value model purposefully to assess performances and efficiencies of innovative AI tool implementation, namely automation of decision-making in fintech (Fig. 1).

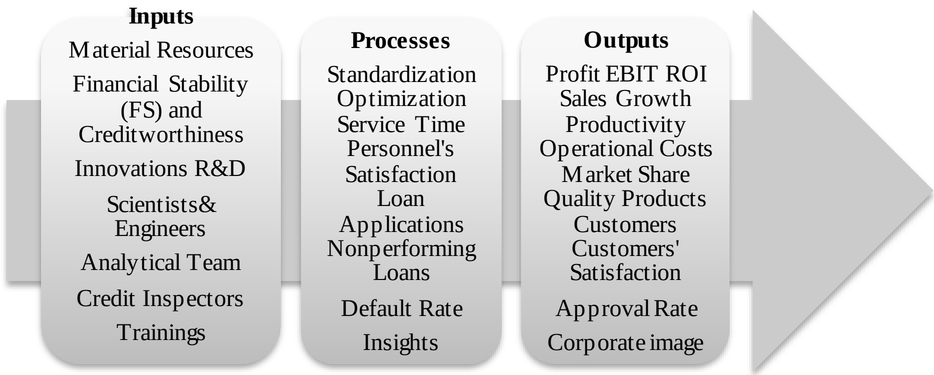

Fig. 1. General Business Value Model of Decision-making Automation in fintech

Key financial services opportunities in the lending subsector enabled by AI are gradually developed from (i) providing just-in-time lending and (ii) miniaturizing unsecured lending to be user-specific, (iii) providing real-time personalized practicable advice, (iv) offering tailored, always-on experiences across channels, (v) predicting with greater accuracy defaults, to (vi) automating and augmenting business credit decision-making and, (vii) improving client advisory by integrating into data streams for opportunity discover [19]. It is progressively or parallelly evolving developments and strategies incorporating the 'lean culture', faster and leaner operations using automation to improve the efficiency of business processes, reduce costs, improve quality of customer experience, tailored products and advice to making services available to preferred customers' formats and channels, and expand offering geographically.

We assume that the methods we studied and the proposed generalised business value model allow us to achieve the following improvements:

(i) reduced time from 15 minutes or more to instant decision making, (ii) decreased nonperforming loans rate, (iii) increased completely non-human based decision making to 70% or more, (iv) reduced operational costs, (v) multiplied processing number of credit applications, and (vi) retained or maintained more than 90% customers satisfaction levels, all in context of dynamic market expansion.

These improvements are cumulatively key high-efficiency indicators of AI automated decision-making in the financial industry.

4 Fintech Case Study

In Bulgaria, the fintech sector of nonbanking lending grows up quickly. Since 2009 the number of registered financial institutions with main business activities of granting credits with funds that are not raised by a public attraction of deposits or other repayable funds, and financial leasing, almost triples reaching in totally 190 in 2018 [20]. The competitive environment is replete with more than 40 nonbanking financial institutions providing short-term credits highly active on the market. The level of crediting remounts the pre-crisis level of around 1 300 bln. EUR maintaining 2,3% to 2.7% of GDP in the last four years. The growth is 17,82% for the period of December 2012 to December 2018. In the same period the growth of lending for more than five years is most significant (69,85%), followed by credits providing up to 1 year (46,01%) and credits for 1 to 5 years (4,42%) [21]. Another trend that stands out is the considerable and progressive turndown of nonperforming loans, dropped to 8,9% in December 2018. The overall drop is 46,09% for the considered period of December 2012 to December 2018. From its highest level in mid-2014 the turndown is 65,72%.

For present research, we study a Bulgarian digital native organisation that is one of the fastest growing fintech structures nationally developing innovative services adapted to the modern digitally empowered world. Founded in 2007 it provides financial services as a non-banking crediting institution, focused on short-term credits and instalment credits. Six years later it enters the online microcredit market becoming a leader on the online credit market. Nowadays it operates entirely online. The financial services portfolio includes classic products as “credit to salary” to provide loans from 50 EUR up to 400 EUR within a 30-day payout free period and “credit plus” to provide loans from 100 EUR up to 1 500 EUR with payment deadline from 3 to 24 months [22]. The “car leasing back” up to around 15 000 EUR for long-term financing is another lending service that diversifies the value proposition of the brand.

The business model settles on cutting-edge technology solutions and services, real-time instantaneous online lending, low operating costs and economies of scale and experience. The organisation proactively monitors the technological tendencies of the business environment to implement innovative solutions rapidly so to respond to the industry's competitive dynamics and customers’ expectations and to acquire distinctive competitive advantages. To demonstrate it, we summerise the leading technologies and business developments since 2013 in Table 1.

Table 1. Technologies and Business Developments in the period 2013 – 2019

Year	Technologies & Developments
2013	▪ Fully online operations
2014	▪ Mobile expansion (iOS and Android applications)
2015	▪ BB+ long-term rating with a stable perspective and B for short-term Credit rating Certification by Bulgarian Agency for Credit Rating (BACR) valid in EU
2016	▪ A long-term rating with a stable perspective and A-1 for short-term Credit rating Certification by BACR ▪ Chatbot on Messenger for Credit provision

	▪ New product "pay after" for Online marketplaces ▪ Business expansion to Macedonian market
2017	▪ Bitcoins instalments payment ▪ Instantor application verifying Client's bank account ▪ AI Credit score as a Service ▪ Top 10 Alternative financing companies in Europe by European Fintech Awards 2017 for European Innovators 2017 ▪ New product "car-leasing back" ▪ Business expansion to the Polish market
2018	▪ Instant Real-time Loan Approval (First provider on the market) ▪ Up to 60% applications without human intervention (Q3 2018) ▪ Credit inspectors' staff: -50% ▪ A+ long-term rating with a positive perspective and BBB+ for short-term Credit rating Certification by BACR (highest in Bulgaria) ▪ Business expansion to the Colombian market
2019	▪ Users/Customers growth to 4000000 ▪ Up to 100% applications without human intervention (Q1 2019) ▪ Business expansion to Spain market ▪ Chatbots on Viber, WhatsApp, and Skype (expected)

The overall business processes of credit application and approvals are organised online and managed through a customer-oriented innovative platform for complete management of real-time high-speed 24/7 credit application processing. It represents a fully automated instant decision-making. The information system is empowered by multiple innovative AI's solutions to provide fully online operations in customers friendly and efficiency purposeful manner such as chatbot for automatically completion of the credit application form being a capable instrument for timesaving and mistakes-reduction due to incorrect or unclear data provision and, cloud-based AI's powered real-time credit scoring as a service. The ladder aims to maintain or increase the competitive advantages in a fast-growing competitive environment and to improve the efficiency of the business processes by (i) increasing the approval rate of credit applications, (ii) reducing the human factor in lending decision making processes. The AI solution automates the decision-making process of lending approval generating a scoring model that provides an instantaneous scoring of customers. It assesses the creditworthiness of the loan applicants enabling it to determine how likely a lender will default its loan. Also, the factors affecting the probability of a borrower falling into default are identified defining optimal scoring values, which improve the capacity of the credit inspectors to accept or reject the application (if human intervention is needed). There is an optimal selection of borrowers determined by the business risk management and profit strategies of the financial institution.

The AI solution is a machine learning scoring process, which is a method of designing algorithms (sequence of actions to solve a problem) [23]. Self-learning algorithms are integrated. They are continually fine-tuning themselves in order to give the optimal cutoff. There is a learning process founded on recent customers' behaviour. It uses historical data about the applicants and integrates knowledge about customers or best practices into automated scorecard development. So, it optimises automatically on biweekly bases or less based on experience, limited or no human intervention. It is used to find patterns in a large quantity of data. The patterns identified, correlated with other events or patterns, are not readily visible but help to understand complex relationships. It utilises different data sources, besides historical data, also open source data and different types and quality (structured and unstructured) data. Credit history and personal data are mathematically modelled; the modelling relies on quantitative and qualitative data; collected data are from social media, location-based, networking, and online shopping behaviour, others. Up to 20000 data points are used to calculate credit score in seconds. It provides real-time decisions based on the most significant variables extracted out of existing data. AI-powered credit scoring is a tool to increase the approval rate and to reduce defaults. Beyond the static scorecards, it can quickly implement new data points to improve the credit scoring model performance. The model is adapted to the business logic, needs and rules of the lending organisation and is further improved and refined during the performance.

We identify multiple advantages characterizing the AI-powered decision-making process, such as (i) accuracy and reliability of up-to-date decision-making integrating business core specificities, (ii) agility and flexibility with multiple scorecards support applying different characteristics sets, (iii) velocity as real-time decision-making, (iv) economy and efficiency with minimum initial costs and operating costs reduction, (v) ease and accessibility (easy use and no need for knowledge engineers or specific technical knowledge staff) [23]. All of them lead to a sound increase in price and non-price competitive advantages of the lending institution. The easy-to-use and easy-to-adapt platforms facilitate and favour the velocity of the expansion and entry to new markets. Another significant benefit for customers is that the data are received and processed in an environment, completely protected from human intervention.

Having 1000 customers in 2009, 5000 in 2010, 200 000 in 2014, the company reaches 4 000 000 credit applications processed as of February 2019. It is a four-time multiplication of the volume of loans applications processed in last year. Already, in 2017, the net profit of the company amounts 6.9 million BGN with a loan portfolio of 23.4 million BGN, a rise of 154% in comparison with 2016. Respectively, increases of 29% of the loans provided, 26% of net interest income, and 27% of other operating incomes are observed; the overdue and impaired loans rise with 33%, but the losses from impairment and uncollectibility of loans diminish with 35% [24].

For 2018 the company records asset value growth and reports to maintain excellent levels of financial performance.

Following the general business value model, we find both quantitative and qualitative evidence and outcomes for high efficient automation of decision-making. Thus, thanks to this, we have developed and proposed the specific variant of Business Value Model, which can serve as a generalised AI application scheme for other similar companies (presented in Fig. 2). The innovation implementation does not require additional material resources (premises, others), neither R&D activities nor attraction of specialised staff (analytical staff, scientists&engineers). The organisation provides basic training on the system's functionalities. The labour costs of credit-scoring department diminish by 50%. There is a reduction in operating costs, also a 5% reduction of nonperforming loans. More than 70% of decision-making is non-human based practically. Personnel satisfaction is augmented, and the customers' satisfaction is as high as 96%.

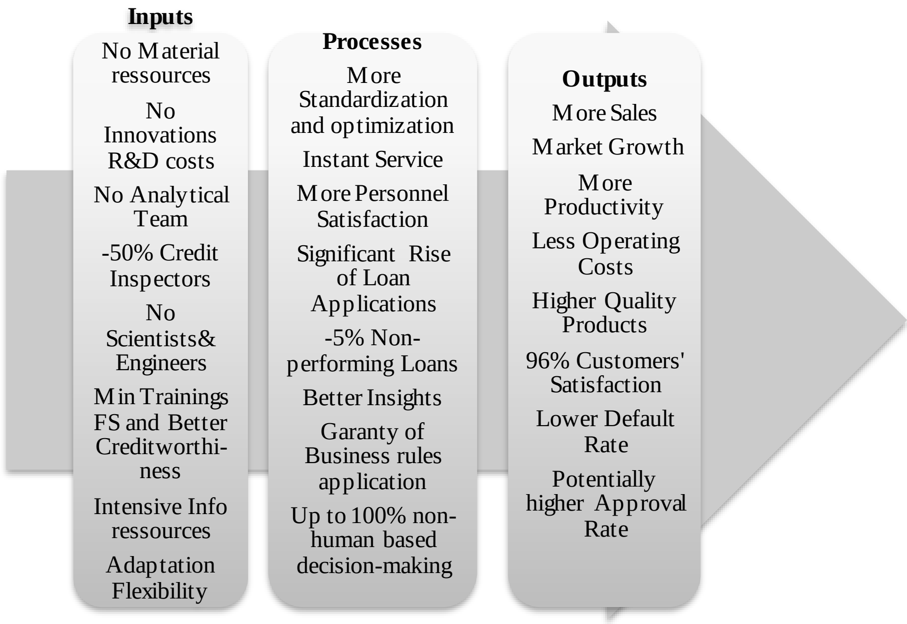

Fig. 2. Detailed Business Value Model

5 Conclusion

The intensification of cognitive technologies and AI-based data driven-decision making application in the financial industry leads to improvement of overall organisational efficiency and performances, assuring higher quality products, less operating costs, more customers and personnel's satisfaction. The studied financial institution demonstrates sound performances for all established fundamental high efficiency indicators of AI automated decision making, namely: (i) reduced time to instant lending decision making, (ii) nonperforming loans rate at -5%, (iii) completely non-human based decision making up to 100% in 2019, (iv) reduced operational costs including redaction with 50% of credit personnel, (v) four times multiplied processing number of credit applications up to 4 mln. in 2019, and (vi) maintained 96% customers satisfaction levels, while market expansion occurs.

Clearly, the AI implication solutions studied (i) meet the five criteria of useful information needed to perform quality decision-making, (ii) extend the knowledge base and secure the rationality of decision making as a specialized expert system, (iii) outperform programmed decision making both carrying it from risky towards certainty context, and avoiding irrationality in information asymmetry, (iv) institute confidence for credit extension, (v) ensure velocity, adaptability, focus and flexibility in demanding competitive environment.

Based on the analysis of a specific credit institution, as well as an analysis of the use of AI in the industry, we have formed a Business Value Model, which can be used in many enterprises. It can serve as the generalised AI application scheme and be adapted for other similar companies and credit organisations.

However, more extended monitoring period since the implementation of the innovation is needed in order to study and evaluate all components of the business value model promptly and validate the efficiency and sustainability of the business results. The developed in the current paper business value model, as well as the provided analysis and approach, will further enhance the applied efficiency management framework of the company to pursue towards a more complex method of assessment of performances and efficiencies.

Also, proactive strategies allow anticipated competitiveness. More powerful computation inflicts higher standards for AI. Next trends already expand the evaluation of the price of credit contracts. New emerging differentiators for attracting customers such as customization (optimize financial outcomes by advising customers, competing on value offered), capturing attention (services beyond financial), developing ecosystems (more data - better advice and performance) replace the historic differentiators relying on price, speed and access [19] as demonstrated in current case study. Further, the expectations are that the AI drives shifts in customers' behaviour and operating economics that will favour scale players and agile innovators or niche players restructuring the market [19]. All these developments could be taken into consideration by the company in a short period in order to maintain sustainable competitiveness in the dynamic financial sector.

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