SECURE II: Unlocking the Potential of Artificial Intelligence for Entrepreneurial Success

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Abstract

This study explores the potential of artificial intelligence (AI) in assisting novice entrepreneurs in evaluating the effectiveness of ex-ante measures of business model design and their impact on ex-post measures of performance. The study adopts a decision science approach to argue that entrepreneurs create business models by making choices based on what is valuable and possible rather than what is available. The Startup Evaluation Calculus with Research Evidence (SECURE I) framework has shown that the careful design of ex-ante measures can positively impact ex-post standards of firm performance. The study proposes a SECURE II framework integrating AI tools to improve the frameworks' predictive ability. By unlocking insights and patterns hidden in large volumes of data, AI can assist entrepreneurs in making informed decisions and becoming more responsive and agile to market needs. By unlocking patterns hidden in voluminous data, AI can assist entrepreneurs to predict Entrepreneurial Capability for making informed decisions and becoming more responsive and agile to market needs. The study's contributions include integrating Symbolic AI and Neural AI to aid entrepreneurial decision-making, enhancing the cognitive capacity of decision-making, and using an evaluation tool that incorporates automation and persuasiveness. The research relies on quantitative data and uses an experimental method to examine the effects of AI on entrepreneurial decision-making.

Keywords: Entrepreneurship; Artificial Intelligence; Machine Learning; NSAI; Startup; Sustainability.

Introduction

This study explores the potential of artificial intelligence (AI) in assisting novice entrepreneurs in evaluating the effectiveness of ex-ante measures of business model design and their impact on ex-post measures of performance. Shafer et al. (2005, pp. 199-207) describe a business model as "a representation of a firm's underlying core logic and strategic choices for creating and capturing value within a value network." The study adopting the design science principle argues that entrepreneurs design business models by choosing what is possible and valuable rather than what is available (Magistretti et al., 2023; Seckler et al., 2021). All novice entrepreneurs start with designing the business model for their proposed ventures. However, while planning their business models, novice entrepreneurs are unsure of the effectiveness of ex-ante business model measures and their actual effect on the ex-post measures of performance outcomes. Therefore, little assistance is available to novice entrepreneurs in evaluating these proposed ventures' desirability, feasibility, and viability (Arshi et al., 2020). In such cases, Artificial Intelligence (AI) assisted assessment of business models can help novice entrepreneurs evaluate the effectiveness of ex-ante measures of business model design and their effect on ex-post-performance measures.

Artificial intelligence (AI) is generically defined as "the imitation of human cognition by computers" (Jha & Topol, 2016, p. 2353). Further, Schmidt et al. (2020), focusing on AI capabilities, defined AI as *the ability of organizations to use data, methods, processes, and people to create new possibilities for automation, decision-making, and collaboration that would not be possible by conventional means*".

SECURE I (Startup evaluation calculus using research evidence I), a new business model framework to measure startup performance, has demonstrated that careful design of ex-ante measures of business models can positively impact ex-post standards of firm performance (Arshi et al., 2020). Reinforcing these findings, SECURE II (The startup evaluation calculus using research evidence II) augments the BM ex-ante measures' predictive ability on startup performance by integrating AI tools into the framework. The significant benefit of using AI-enabled SECURE II is that it can unlock insight and patterns hidden in large volumes of data and make informed startup persuasion decisions (Mikalef & Gupta, 2021) by offering ‘Entrepreneurial Capability’ as the probability of a venture succeeding. Furthermore, according to (Keding, 2021), AI-enhanced informational effects on market knowledge improve the quality and speed of decision-making as entrepreneurs respond more and more responsive and agile to market needs and problems. According to Wamba-Taguimdje et al. (2020), t*he* informational effect refers to the ability of AI to collect, store, process, and disseminate information that is current, reliable, available, complete, relevant, and dynamic. Finally, the rationality within the AI tools can help entrepreneurs systematically and effectively identify patterns and signals sometimes missed by the human mind (Eriksson et al., 2020).

Review of Literature

Quest for Artificial Intelligence

According to Russell et al. (2015), success in the quest for Artificial Intelligence has the potential to bring unprecedented benefits to humanity. Therefore, exploring ways to maximize these benefits via research is worthwhile. The growing capabilities of AI are leading to a more significant impact on human society. Artificial Intelligence (AI) is software that imitates human intelligence (Yang & Siau, 2018) and uses computer science, mathematical formulas, statistical models, and data science to solve complex problems. As it can carry out time-consuming and sometimes even impossible tasks (Konar, 2018) indicates, calling it 'Artificial' was not prudent. While McCarthy (1987) devised the term "Artificial Intelligence," its inference as ‘a computer program with common sense was conceived’ with inferiority in comparison to human intelligence (Partridge & Hussain, 1992). Although AI was established as a discipline in the 1950s, it was not until the 1980s that it saw its first commercial application (Schoech et al., 1985). Since then, thanks to Moore's Law (1965)which describes the exponential growth of available computing power, its success has accelerated.

As we live in a world of hyper-connectivity and hyper-automation where the industrial revolution facilitates human-computer interaction and altered logic of business models (Schwab, 2017), AI can be the solution to redefine and transform relevant management processes (Kolbjørnsrud et al., 2016). It uses computational methods created through "experiences" or data and with statistical techniques (such as classification, regression, ranking, and clustering) to conjure the algorithms to make accurate predictions (Scott & Scott, 2002). According to Soni et al. (2019), AI transforms businesses in three ways. Firstly, it helps enhance interaction and experience using AI agents. Secondly, it processes data to facilitate the prediction of events, and thirdly, it supports transformation in human skills.

Murray (2018) estimates that a significant stake in global companies would use AI to redesign business operations. Medical sciences (Jiang et al., 2017); social sciences (Sartori & Theodorou, 2022); marketing (Kumar et al., 2019), and finance (Kumar et al., 2019) are all examples of the ever-evolving industrial applications impregnated by AI (Faccia et al., 2019). Furthermore, AI allows firms to conduct supply chain analysis (Laínez & Puigjaner, 2010) and product development (Metaxiotis et al., 2003). Although Artificial Intelligence (AI) is a business-disruptive technology, it has developed in an unstructured manner in the academic and professional literature (Sestino & De Mauro, 2021). As per Mishra and Tripathi (2021), AI has incorporated its use to instrument state-of-the-art business models. As a result, companies have identified commercial opportunities to boost competitiveness and re-engineer products or services (Wamba-Taguimdje et al., 2020).

According to Unhelkar & Gonsalves (2021), AI can be used to rethink corporate strategy to assist firms in solving problems and fostering critical thinking. Businesses can adopt a comprehensive approach to business optimization by examining business strategy, business process modeling, and quality assurance to increase customer value and profits eventually. According to Galanos (2019), businesses increasingly depend on artificial intelligence (AI) to increase human comprehension of complex systems and automate decision-making. The availability of silos of dynamic information flow stimulates a greater focus on AI applications based on intelligent algorithms, which has implications for both business and society (Chalmers et al., 2020). According to Corea (2019), the ultimate goal of this embryonic technology in business is to look out for advanced cutting-edge research in the fields of AI as well as interrelated arenas. In this manner, when real-time data analytics are cohesive into business processes using AI, it would further lead innovation to develop impactful ways to advise businesses with actionable tasks and probable impact (Charif & Awad, 2014).

Artificial Intelligence (AI) techniques

Since its inception, Artificial Intelligence (AI) research has looked at a wide range of issues and methodologies. Given how quickly AI research is growing, there is widespread agreement that its societal effect will expand. Because of AI's potential, exploring ways to harvest its benefits is essential while avoiding its drawbacks. AI supports data-driven approaches that try to predict the future based on historical and current trends. Specifically, it leverages 'proven links between explanatory and criterion variables from previous occurrences to predict future outcomes' (Cowls et al., 2023).

Russell et al. (2015)'s research priority for optimizing AI's economic impact concentrates on industrial applications of AI, from manufacturing to information services, which have an increasing economic influence. Economists feel that more research is needed to maximize the economic benefits of AI while minimizing its negative consequences, which has prompted a variety of research fields ranging from economics to entrepreneurship. It also confirms that AI can be applied for labor market forecasting, analyzing other market disruptions, exploring significant policy impacts, and further predicting economic measures.

Artificial intelligence (AI) is a broad term that refers to a variety of terminologies, including Machine Learning (ML) and Deep Learning (DL) techniques (Kitchin & Lauriault, 2015; Russell & Norvig, 2013). ML and DL strive to iteratively evolve a knowledge of data without deciphering any rules, whereas traditional AI issue-solving relies only on specific techniques. This enables the system to learn and produce predictions automatically, altering their parameters as needed by optimizing a performance criterion and lowering the error rate at each learning stage (Alpaydin, 2016). ML is carried out by estimating mathematical functions that uncover representations of some input to construct predictions on new data, which is commonly done on larger datasets (Di Franco & Santurro, 2021).

As a result, the amount and quality of data to which a model is exposed determines how much it learns. Simultaneously, recent Deep Learning successes in image analysis and speech recognition have attracted widespread interest, with Deep Learning appearing to be the model of choice in various sectors (Yang et al., 2021). DL models are one of the most rapidly evolving Artificial Intelligence (AI) methodologies, and they appear to be driving the development of most sectors (Tang et al., 2022). According to Di Franco & Santurro (2021), ML provides a comprehensive range of mathematical tools for dealing with various situations. The key tool is artificial neural networks (ANNs), a complex modeling tool for describing non-linear functions, which is common in real-world applications. ANNs are made up of simple processing components known as "artificial neurons," which are activated by a function known as the "activation function."

ANN provides a range of algorithms that can address cognitive tasks where it processes aggregated data and imitate human actions. ANNs can be either supervised or unsupervised and extended as Hybrid models for enhanced accuracy (Abiodun et al., 2018). Due to labeled datasets, supervised learning data sets are more accurate in prediction than unsupervised ones. In contrast, unsupervised learning models are good at understanding large sets of unlabeled data in which the algorithm finds hidden patterns which are difficult to fathom. Apart from supervised and unsupervised, a hybrid learning model can also be devised using a labeled and unlabeled dataset (Liu & Xiang, 2017). ANNs are capable of universal approximation and have a flexible structure that allows them to capture complex non-linear behavior. Given the correct training algorithm, transfer function, and the model's learning rate and momentum, it can forecast accurately (Velasco et al., 2018).

ANNs comprise three layers of neuron structures: input, hidden (middle), and output. The input layer collects numerical data with feature sets and activation values in the form of feature sets and activation values. The hidden layer receives input values from the linked neurons. The input neurons are totaled in the hidden layer to compute the weighted sum of the input neurons, and the summed neurons are then merged in the output layer to produce results using an activation function (Lau et al., 2019). Connections between neurons are frequently coupled with coefficients or weights modified by training algorithms. Neurons oversee eradicating database anomalies and storing network knowledge. As a result, ANNs are capable of adaptive learning self-organization and have a resilient structure with parallel distribution layers. Besides being tolerant to outliers, ANN can model different variables, and their non-linear relationships can further enable quantitative and qualitative variable modeling (Alcañiz et al., 2023).

Deep learning is a branch of artificial neural networks that process data using multi-layered neural networks. Deep neural networks work on the principle that each hidden layer, starting with the raw input, combines the values from the previous layer and learns more complicated input functions. As a result, the meaning of raw input data is complex for a computer to comprehend. This problem is solved by splitting the intended tasks into several nested concepts, each specified by a separate layer of the model (Di Franco & Santurro, 2021). Deep Learning networks have been trained to identify voice, caption photos, and translate text between languages. However, Dep Learning models' mathematical and computational methodology is complicated to decipher, especially for interdisciplinary scientists ((Emmert-Streib et al., 2020). Thus, despite the widespread use of Deep Learning networks to solve real-world problems, we still don't fully comprehend why they are so effective.

Furthermore, as per Garcez & Lamb (2023), there is a difference between having neuronal and symbolic modules that communicate in various ways and have evolved from one representation to the other in a more integrated fashion. Hence, according to Sejnowski (2020), a considerably larger spectrum of architectures is required to produce autonomous AI systems. This study combines robust neural network learning with suitable reasoning via symbolic representations for network models. Despite their unquestionable success, traditional Deep Learning architectures have several drawbacks, including data inefficiency, brittleness, and interpretability. These restrictions call for the necessity for well-founded knowledge representation and reasoning, as stated by scholars, must be merged with deep learning for sound explainability. In such cases, Neuro Symbolic AI can be a powerful approach providing cognitive modeling capable of achieving artificial general intelligence. According to Susskind et al. (2021), Neuro-symbolic models have already demonstrated the capability to outperform state-of-the-art deep learning models in domains such as image and video.

Neuro Symbolic AI

As per Siyaev et al. (2023) Neuro Symbolic Artificial Intelligence (NSAI) is an emerging area of research that combines the strengths of symbolic reasoning and neural networks to achieve more robust and explainable AI systems. In recent years, NSAI has gained significant attention in the AI research community due to its potential to address some of the challenges associated with conventional machine learning techniques, such as data scarcity, generalization, and explainability (Linardatos et al., 2021). One of the main approaches in NSAI is to integrate symbolic reasoning into neural networks. This involves incorporating symbolic knowledge, such as rules, constraints, and logical relationships, into neural networks to improve their reasoning capabilities. For instance, the Neuro-Symbolic Concept Learner framework proposed by Liang et al. (2022) combines a neural network with a symbolic rule learner to learn symbolic concepts from data. The resulting model achieved state-of-the-art performance on several benchmark datasets while maintaining interpretability (DeLong et al., 2023). Another direction in NSAI is to use neural networks to learn representations that can be easily interpreted in a symbolic framework. For example, the Neuro-Symbolic Program Synthesis (NSPS) framework proposed by Parisotto et al., (2020) learns a neural embedding of program syntax that can be used to synthesize programs from natural language specifications. The NSPS framework achieved state-of-the-art performance on several program synthesis benchmarks while providing interpretable program outputs to address some of the limitations of conventional machine learning techniques.

AI in Entrepreneurship

According to Lee et al. (2019), the proactive application of AI can drive business model innovation. As reflected by researchers, the most prominent usage scenarios could be forecasting the assessment of business strategies (Verma et al., 2021) to extract subjective information about a business (Rambocas & Pacheco, 2018) and risk evaluation (Khalid et al., 2022) of a company. Machine Learning, Fuzzy logic, and Artificial Neural Network (ANN) algorithms embedded in AI can identify valuable insights and when exploited, can sufficiently predict the impact on both the success & profitability of a business (Reutterer et al., 2017). Additionally, it can automate the detection of potential anomalies in business processes (Rogge-Solti & Kasneci, 2014) and offer guidance, as reflected in the presented study. Nascent entrepreneurs' success in launching a new venture depends on the feasibility and viability of their business models. Therefore, business models are essential for starters to plan new ventures (Foss & Saebi, 2017). In addition, business models help entrepreneurs deal with the uncertainty associated with the complex startup process. However, nascent entrepreneurs have limited resources to develop effective business models and lack the means to evaluate their impact on business performance (Tomy & Pardede, 2018).

Prominent empirical studies on nascent entrepreneurship such as Global Entrepreneurship Monitor (GEM) (Minniti et al., 2005), Panel Study of Entrepreneurial Dynamics (PSED) (Reynolds & Curtin, 2007), and Vienna Entrepreneurship Studies (VES) (Frank et al., 2007) make two observations. One, the startup process is complex and new research should shed light on the decisions of nascent entrepreneurs (pre-business launch design). Second, the founding success of nascent entrepreneurship is linked to recent venture performance and survival. However, when these nascent entrepreneurship studies were conducted, AI was not fully developed to solve problems with budding entrepreneurs.

Addressing this issue, Gottlieb & Rifai (2017) highlighted the critical role of data analytics in business model design. They associated it with founding success and new venture survival and growth. Furthermore, Wixom & Ross (2017) buttress the cause of utilizing AI-driven data analytics in improving business robustness in two ways. Firstly, informing the decision-making related to its ex-ante measures and improving BM's evaluation of ex-post outcomes. Similarly, Hosaka (2019) argued that AI-based tools better predict outcomes as they are less reliant on human judgment and can detect patterns that may be too subtle for human cognition. Fruhwirth et al. (2020) further argued that novice entrepreneurs require innovative tools that integrate the views of data and analytics. The authors maintained that data analytics could leverage Business Model's capacity to produce desired outcomes in outcome-driven business models.

According to Szopinski et al. (2020), software and digital tools help design effective ex-ante business model measures. When AI and digital tools are utilized, data becomes an essential resource for improving confidence in Business Model parameters (Engelbrecht, 2016), and ultimately AI can have interesting business implications.

Research Gap

Most AI studies have focused on integrating AI in different business models and on the role of AI in business model innovation or demonstrating how AI technology has enabled existing firms to design business models for the digital era (Mishra & Tripathi, 2021; Sjödin et al., 2021). However, existing research does not shed much light on how AI can improve novice entrepreneurs' confidence in the business model's ability to predict performance and improve startup persuasion decisions. Hence, we've come up with the following research questions -

Research Questions

1. *How can AI enable novice entrepreneurs to assess the effectiveness of ex-ante measures of a business model and their effect on ex-post performance measures?*
2. *How can artificial neural networks (deep learning) reduce data uncertainty by classifying and predicting Business Models' ex-post measures (desired financial outcomes)?*
3. *Can AI help eliminate data uncertainty and improve confidence in entrepreneurial decisions to launch startups?*

Contributions of this study

SECURE II framework integrates Symbolic AI and Neural AI to aid entrepreneurial decision-making in launching startups. It enumerates how Symbolic AI and Neural AI tools and techniques can help novice entrepreneurs reduce data uncertainty and improve the robustness of ex-ante measures of business model design. Such an approach compensates for Gestalt's view, which implicitly assumes that human cognition is deficient in understanding images and words.

Symbolic and deep neural networks within SECURE II can enhance an entrepreneur's cognitive capacity for decision-making. According to Gestalt's view, entrepreneurs do not see and act based on the opportunities and components of business model design in isolation but together with its potential outcomes. SECURE II provides entrepreneurs with a more competent business model ecosystem and an evaluation tool that integrates automation, connectivity, and persuasiveness to the real world and data intelligence to enhance firm performance.

Research Method

Role of Data Science

The field of Data Science utilizes the ability to analyze large volumes of data in a way that allows hidden patterns to be revealed with unprecedented depth, breadth, and scale (Xu et al., 2021). With just a few disadvantages, the cutting-edge research methodology created and supported by the interdisciplinary approach offers enormous potential to advance conventional social science research (Chubb et al., 2021) in three significant areas. First, by utilizing machine learning techniques and online interactive visualization tools, data science may be leveraged to generate fresh insights for social science. Second, by encouraging free and open-source analytical tools like Python and the development of analytical data pipelines, data science can increase the reproducibility of social research. Third, data science can be utilized to strengthen the reproducibility of social research, expand its ability to assess previously unmeasured behaviors and improve the triangulation of theory. A similar research design has been realized in the given study, where researchers exploring digital phenomena believe that no single truth can be discerned (Quinton & Reynolds, 2020).

The research uses computational modeling that dynamically applies innovative research methodology and differs from the research currently available in the field (Sage, 2020). With more recent advances in visualization techniques and the ability of computers to process and analyze increasingly complex, and growing silos of data, the application of Machine Learning models to support decision-making within an online environment continues to grow (Arshi et al., 2022; Brunsdon et al., 2019). The AI-based SECURE was beta-tested in 5 incubating firms in the given study. In addition, a thousand entrepreneurs evaluated the SECURE II model in UAE, India, and Oman through an online questionnaire where they reflected on the business models in terms of Customer preferences, Costs- based on location, Demand-based on location, Supply chain, distribution, and location analytics, Size of Target market based on location, Sales and Profits, Investment requirements and capital access opportunities, Regulations based on location (refer to https://www.securecanvas.net). The Ease of Doing Business (World Bank, 2019) scale was applied to assess the above.

The collection of data was processed to devise Machine Learning models to be able to test the outcomes. Per the precedent set by Morande (2022), the prediction made using Machine Learning were corroborated for their validity and reliability. Ultimately an integrative scale called Entrepreneurship Activity Score (EAS) was developed using SECURE I (Inputs from the Entrepreneur) and SECURE II (Macro factors relating to a location) that depicted the probability of success rate of a venture.

ML Modeling

The widespread use of statistical learning methods has resulted in effective integration and cross-fertilization across AI, statistics, and other domains. Algorithms that allow for accurate future predictions have been acknowledged as a competitive advantage as they assist in enhanced productivity and improved decision-making (Agrawal et al., 2018). The proposed research peruses a non-traditional method for the fulfillment of objectives. As recommended by Aldridge (2017), without losing sight of research design and underpinning recognition of Machine Learning in literature, it was used as an ‘Innovative Research method.’ The predictive capability of ML offers a more incredible opportunity to present informative insights (Mele et al., 2021). The research follows an exploratory approach that relies mainly on quantitative and symbolic data to draw inferences. *To simplify data processing, symbolic data was converted into quantitative equivalence* (Janetzko, 2001).

The study deployed an experimental method (Blockeel & Vanschoren, 2007; Pineau et al., 2021) that examines the effects of relevant measures to observe the causal effect on the ‘Entrepreneurial Capability’ as a dependent variable (Creswell, 2014). Such methodology is focused on the applicability of Machine Learning models. Its technique comprises an array of computer-intensive methods that aim to discover patterns in data. It uses flexible methods for modeling and offers an expansion to traditional methods, such as regression. According to Morande (2022), the data modeling algorithm corresponded to regression (supervised) and Deepnet (unsupervised) learning mechanisms. According to Uyanık & Güler (2013), regression analysis is a statistical technique that can estimate such relationships among several measures (independent variables) and target values. Further in Machine Learning, as ANN methods are data-intensive, data with a large dataset was used to be able to generate valuable insights. Budding entrepreneurs participated in an online survey (Typeform, 2019) using their mobile devices or computers. The survey also had an embedded workflow that facilitated emailed results post-completion of the survey. Established insights on ex-ante business model measures & ex-post measures of performance were used from SECURE I (Arshi et al., 2020). Considering the nature of RQ, A utility called 'BigML' devised an ML model to fulfill the research objective (BigML, 2016). It also supported developing illustrations of important trends and variations presented in the study.

While preparing the dataset for model training, there were two considerations:

- *Parameter estimates may have a more significant variance*
- *Performance statistics may have greater variance*

Accordingly, Machine Learning utilized the training set and then, from the testing set, recorded the accuracy of the resulting models (Morande et al., 2022). The model Evaluations included an assessment of Performance measures (Accuracy, Precision & Recall) & Confusion Matrix (with F-measure & Phi coefficient) along with Classification thresholds (Graphs) with Receiver Operating Characteristic (ROC) & Precision-Recall Curve (Arshi et al., 2022).

Finally, as Lincke et al. (2021) recommended, the overall Comparison of Evaluation was fulfilled in terms of FPR, % positive instances, Lift, K-S statistic & Kendall's Tau. These models helped make a prediction to address given research questions and reflect on the performance of AI (Garcez & Lamb, 2020; Sarker et al., 2021; Susskind et al., 2021).

Symbolic AI

The research focused on the representation of symbolic AI during Startup Evaluations. Recognizing symbols in graphic documents is an intensive research activity in pattern recognition and document analysis (Lladós et al., 2002). The approach was proposed by (A. d'Avila Garcez & Lamb, 2020) from a practical perspective, the learning was carried out from data by neural networks, and rich first-order logic reasoning and extrapolation need to be done symbolically from descriptions extracted from the trained network. Similarly, while developing Entrepreneurial ventures, the assumption was made to include processes like Construction Permits/ Electricity connections / Property registrations/ Tax management,/ Contract Management as a part of symbolic AI.

According to Hoehndorf and Queralt-Rosinach (2017), Symbolic approaches to Artificial Intelligence (AI) represent things within a domain of knowledge through physical symbols, combine symbols into symbol expressions, and manipulate symbols and symbol expressions through inference processes. They also suggest that in the ideal case, methods from Data Science can be used to generate symbolic representations of knowledge directly. For example, deep Learning methods can identify patterns and regularities within a domain and thereby learn the "conceptualizations" of a domain, and it is an enticing possibility to use methods from Data Science to automatically learn symbolic representations of these conceptualizations (Hoehndorf & Queralt-Rosinach, 2017). It follows the Neuro-symbolic AI initiative adopted by IBM Research (2021) to pursue true natural language understanding via the proxy of question answering. As per the research done at IBM by Roukos et al. (2020) by design, such an approach inherits vital properties of neural nets and symbolic logic and can be used with domain knowledge for reasoning. Moreover, as believed by researchers at MIT (2020), such an approach would make it possible to transfer knowledge across domains where machines can learn more as humans do by mastering abstract concepts.

Measures in the study

Table 1 and **Table 2** represent complex and soft measures used in the study.

Table 1. Complex Measures as Financial Metrics

Metrics	Poor	Satisfactory	Good	Excellent
Cost of Sales (cost-to-sales)	Over 60% of total sales	50-59% of total sales	30-49% of total sales	20-29% (or less of total sales
Gross Margin	Less than 20%	20-40%	40%-50%	50%-70% or more
Operating Expenses	More than 75% of the gross margin	60-75% of the gross margin	40-60% of the gross margin	30-40% or less of the gross margin
Earnings Before Interest, Taxes, and Depreciation	Less than 5%	5-15%	15-25%	More than 25%
Overall, Financial Position	Earnings do not support operations and require continuous infusion of cash	The business makes enough money to cover basic living expenses.	Revenues support payments on debt, pay the owner a good salary, and still have money left in the bank	Revenues support business growth and still have money left in the bank
Profitability timeline	4^{th} year	3^{rd} year	2^{nd} year	1^{st} year

Table 2. Soft Measures as Entrepreneurial Capability

Metrics	Poor	Satisfactory	Good	Excellent
Resource Management	Low level of self-awareness and understanding of business needs	Improved financial literacy to understand resource requirements	Improved capability to leverage personal resources show financial intelligence	Show expertise in leveraging personal resources and mobilizing others to achieve economic and other needs
Ideas and opportunities	Developing basic ideas and imagination to identify opportunities	Developing and exploring new ideas based on identified opportunities for creating value	Valuing and exploiting ideas and opportunities to achieve a vision	Assessing the impact of ideas, opportunities, and actions to achieve sustainable goals
Into Action	Taking initiatives and but high dependence on planning to deal with uncertainties and risks	Improved capability to learn from experience to deal with uncertainties and risks	Improved capability to work in teams, collaborating and networking to deal with uncertainties and risks	Show expertise in making sound decisions about uncertainty, ambiguity, and risk.

Research Model

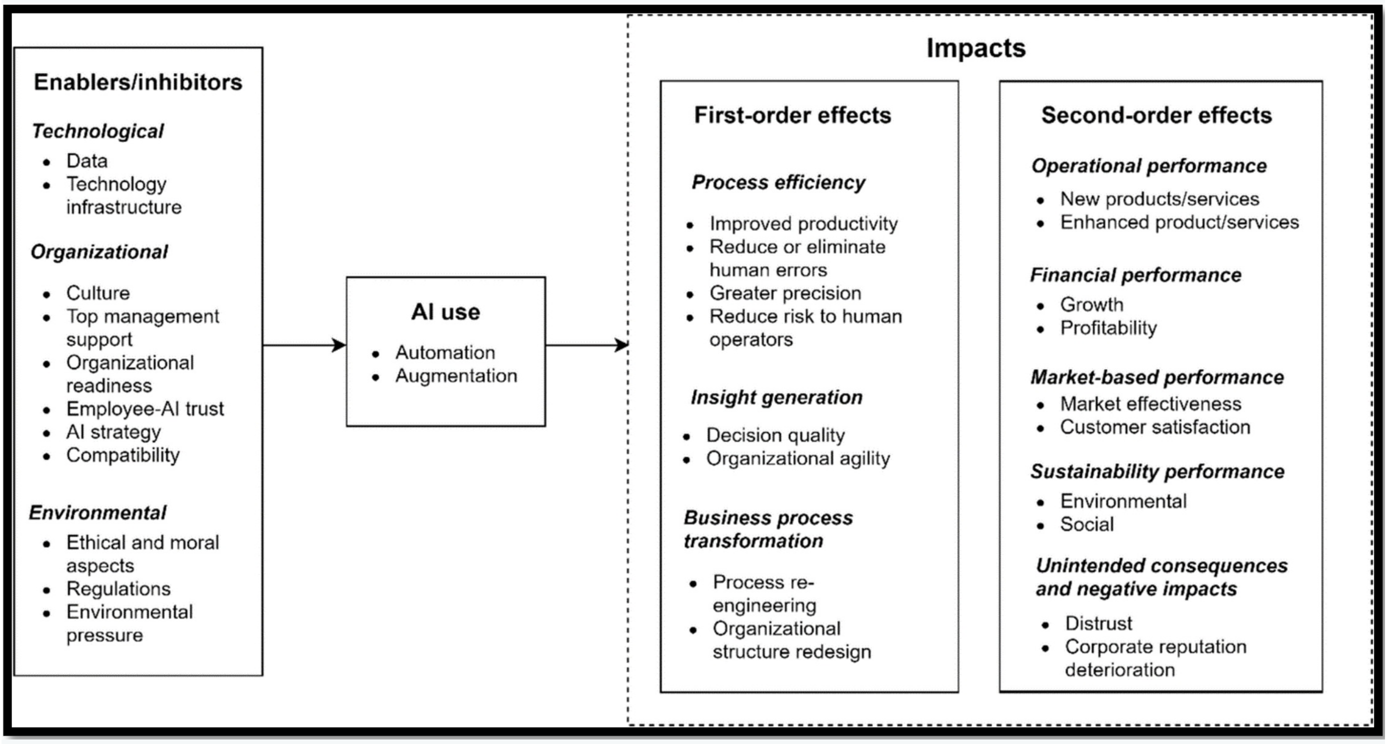

Figure 1. AI Enablers for Automation and Augmentation (Credit: Mishra & Tripathi, 2021)

From this research model, we focus on AI use for*greater precision, reduction of human errors, and improved decision quality* (evaluation of ex-ante measures), which influences proposed*firm performance* (ex-post measures).

Data Analysis

Part I – Logistic Regression

AI being transformational technology entrepreneurship researchers can generate new theoretical insights to develop new pathways for societal impact (Chalmers et al., 2021). Hence based on the ex-ante measures of a business model as Marketability, Viability, Feasibility, Desirability & Scalability in SECURE I (Arshi et al., 2020), their impact can be assessed on Ex-post measures of performance such as Entrepreneurial Capability (Lv et al., 2015). Entrepreneurial Capability is represented in a percentage scale from 0 to 100 as a function of SECURE I Score (Startup evaluation), Location - (origin of a start-up), Entrepreneurship Activity Score (EAS) (consideration of doing business parameters, Predictive Entrepreneurship Opportunity (PEO) (representing assigned weightage to both SECURE I & II) and Global Entrepreneurial Index (GEI) (providing is the overall ranking of a nation.)

In the presented study, the same has been achieved by evaluating the performance of Logistic Regression. During the last decade, logistic regression has been gaining popularity as it is a powerful analytical technique for use when the outcome variable is dichotomous (Peng et al., 2002).

As suggested by Peng et al. (2002) in this paper, the effectiveness of the logistic model was shown to be supported by -

a. Performance Measures (descriptive and inferential goodness-of-fit indices)
b. Regression Model (significance test of each predictor)
c. ROC & PR Curve (predicted probabilities) and
d. Confusion matrix (significance tests of the model against the null model)

The model in **Figure 1** predicts 'Entrepreneurial Capability' using logistic regression. The figure depicts the reflection of the Entrepreneurial Opportunity Score (EAS) on the 'Entrepreneurial Capability.'

EAS is the product of SECURE I & SECURE II that assigns a score based on the Entrepreneur’s knowledge about his/her venture and the Macro conditions around the place where it is being set up.

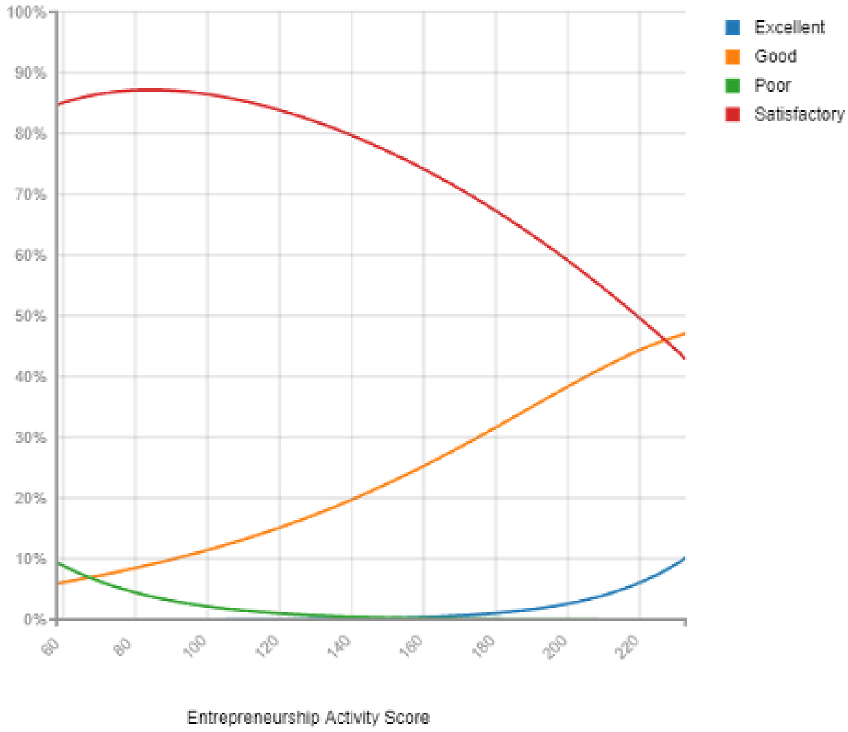

Figure 2. ML Model of Logistic Regression

As shown in **Figure 2** the model shows,

- As EAS increases, the probability of 'Satisfactory' Entrepreneurial capability decreases.
- As EAS increases, the probability of 'Good' Entrepreneurial capability increases.

The results demonstrate that high EAS is preferable while evaluating Entrepreneurial capability. The more excellent value of EAS reflects the enhanced probability that a startup succeeds.

- As EAS increases the probability of ‘Poor' Entrepreneurial capability goes down.
- As EAS increases, the probability of 'Excellent' Entrepreneurial capability goes down.

The probability of 'Good' and 'Satisfactory' Entrepreneurial capability is substantially more significant than the probability of ‘Poor’ and ‘Excellent,' showing 40%-50% of the startups would achieve ‘Good’ and ‘Satisfactory’ Entrepreneurial capability. Further extremes of Entrepreneurial capability (i.e., ‘Poor’ & ‘Excellent’) can be challenging to enhance in a limited time, even with an increased Entrepreneurial Opportunity Score.

As per **Figure 3**, Performance measures of the above model indicate considerably higher accuracy, precision, and recall, indicating the given model's robustness while predicting 'Entrepreneurial Capability.'

79.5% Accuracy	0.6793 F-measure

87.3% Precision	63.7% Recall	0.6459 Phi coefficient

Figure 3. Performance measures with Logistic Regression

F-measure is a means of Precision and Recall, while Phi-coefficient indicates the association between two binary variables, which is significant. Values of F-measure close to 0 indicate the inefficiency of the model and values close to 1 indicate the efficiency and accuracy of the classification model. The confusion matrix shown in **Appendix I** also confirms the higher precision and recall values for all the predicted classes, including for 'Entrepreneurial Capability.'

A confusion matrix is used to measure the performance of an algorithm. An algorithm can classify the data, but it can be misleading if there are unequal classes or observations. It predicts the values based on actual/expected values. Comparison of the actual/expected values with predicted values gives an idea of the accuracy of the classification model.

The confusion matrix calculates the values of precision and recall, which indicates the error and accuracy in the performance of an algorithm.

The ROC Curve in Figure X Curve with “Entrepreneurial Capability” as the target and 'Excellent' as the Prediction Class.

A) ROC Curve B) Precision-Recall Curve

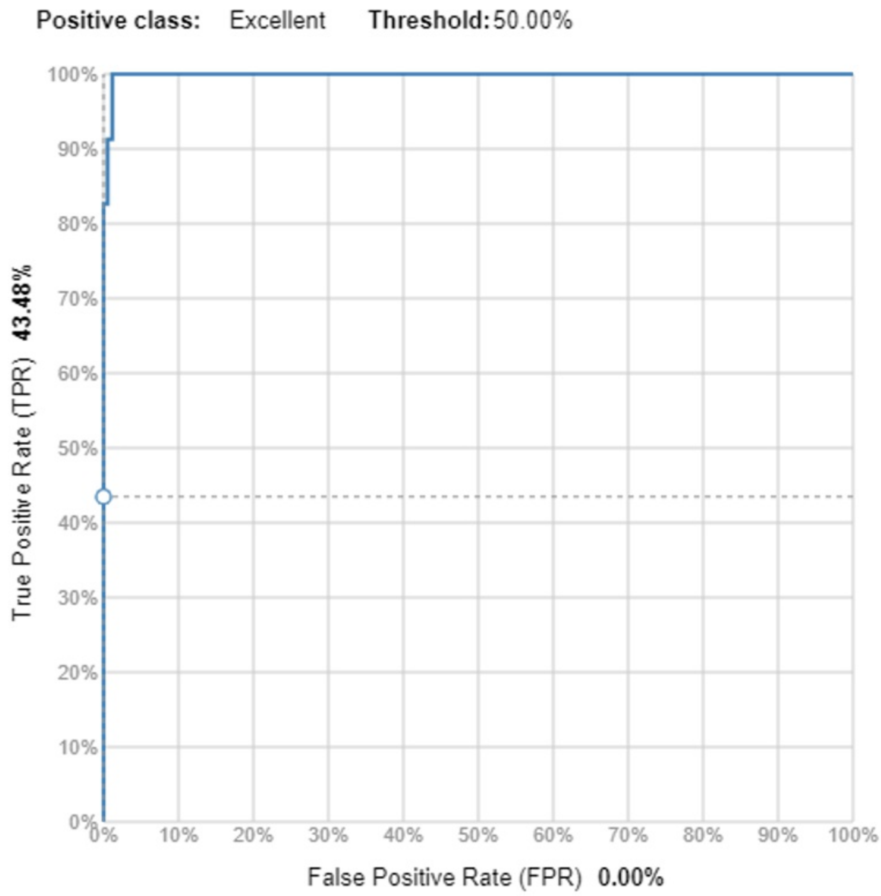

Figure 4. ROC Curve indicating TPR and FPR

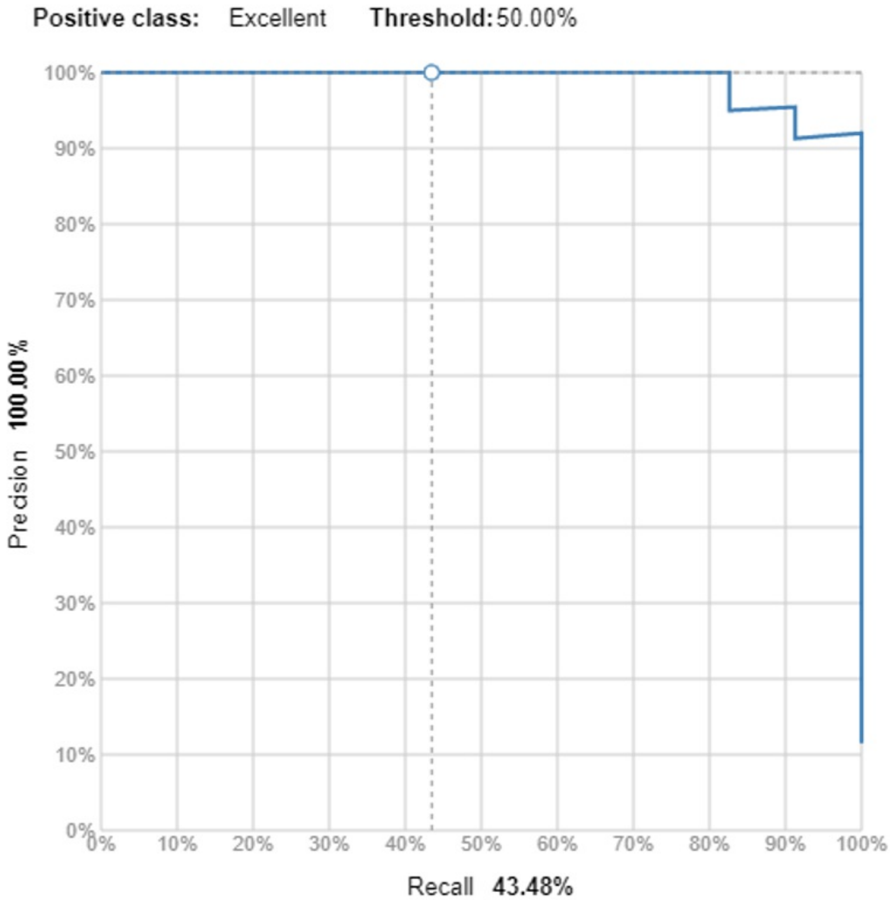

Figure 5. Precision-Recall Curve

False-positive means when the truth is negative, but the test predicts it as positive is called a false positive result. This is also known as a type I error because the test rejects the null hypothesis incorrectly. This type I error is significant in Machine Learning because it measures the accuracy of the result. False positive results give the probability of raising positive results when the valid results are negative.

The above figure (**Figure 4 & Figure 5**) demonstrates a 0% False Positive Rate (FPR) with a 100% Precision and Recall value of 43.48%.

This is because the measure of accuracy (number of predicted values/total number of the sample) can give us misleading results. In contrast, the value of precision indicates the quality of the result. Therefore, it is measured as True Positive/True Positives + False Negatives, which gives us the result of only relevant true/correct positives instead of all the positives in the data.

Part II – Neural Networks

Artificial Neural Network (ANN) in **Figure 6** has been built with the ADAM algorithm using 2 Hidden Layers indicating Financial Metrics plotted against SECURE I (x-axis) & SECURE II (y-axis).

The neural network has been represented as a Partial Dependence Plot (PDP). A partial Dependence Plot depicts the functional relationship between a small number of input variables and predictions.

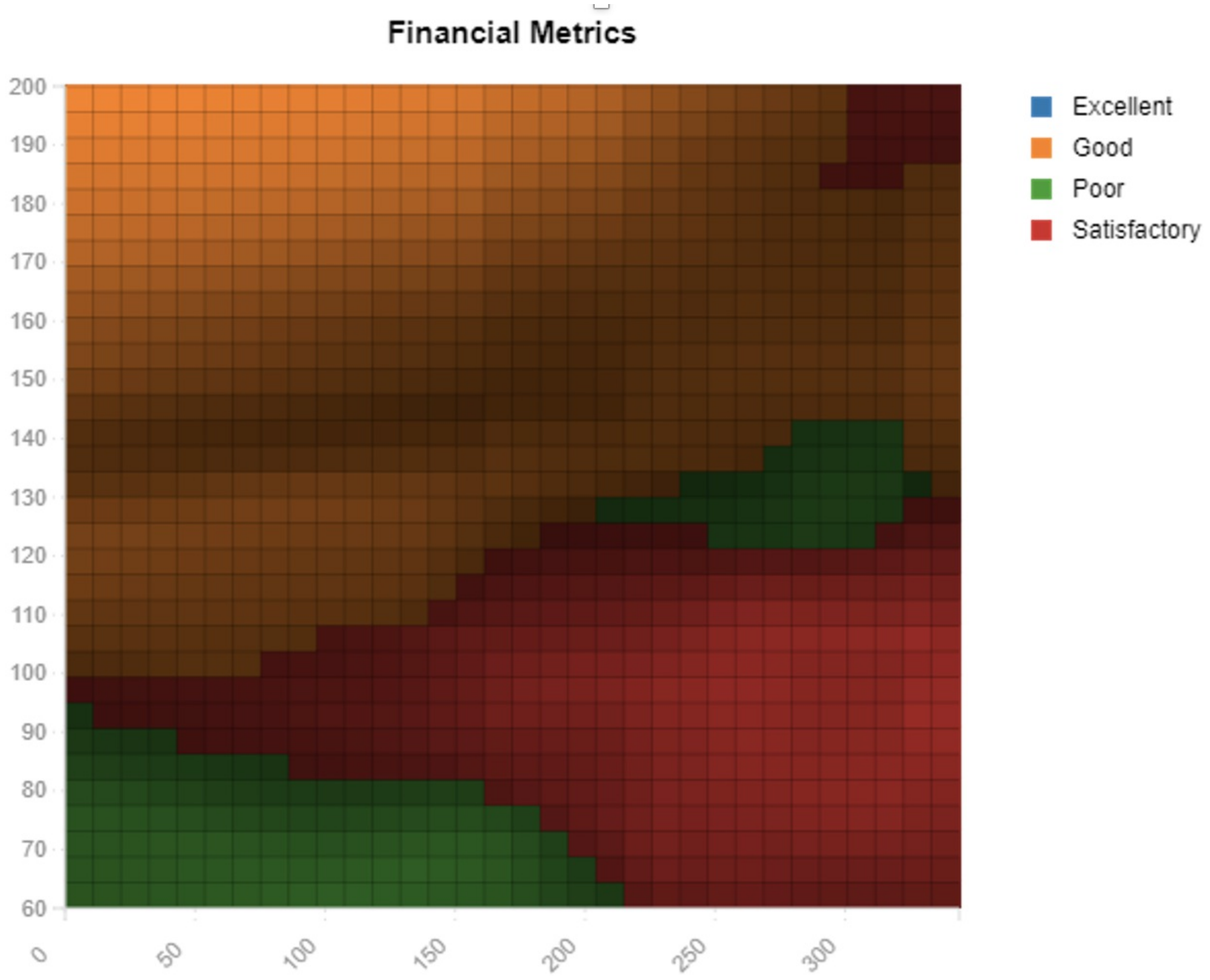

Figure 6. Neural Network indicating 'Financial Metrics'

The above Partial Dependence Plot shows a majority of the area being covered with 'Good' and 'Satisfactory' 'Financial Metrics.' While 'Poor' Financial Metrics result from lower SECURE I & II values covering large areas, the plot (or possibility) of 'Excellent' Financial Metrics is minimal based on **Figure 6.** Model summary indices of Neural Networks in **Figure 7** further indicate that Entrepreneurial Capability (13.83%), S1M3 (Feasibility 12.435) & S2 (SECURE Canvas 10.55%) play a significant role in predicting Financial Metrics. SECURE Canvas is a snapshot of a business model presenting Activators (Business idea, Promotion Mix) Facilitators (Resource & Competencies), and Differentiators (Service innovation, Competitive advantage) possessed by a startup (Arshi, 2019).

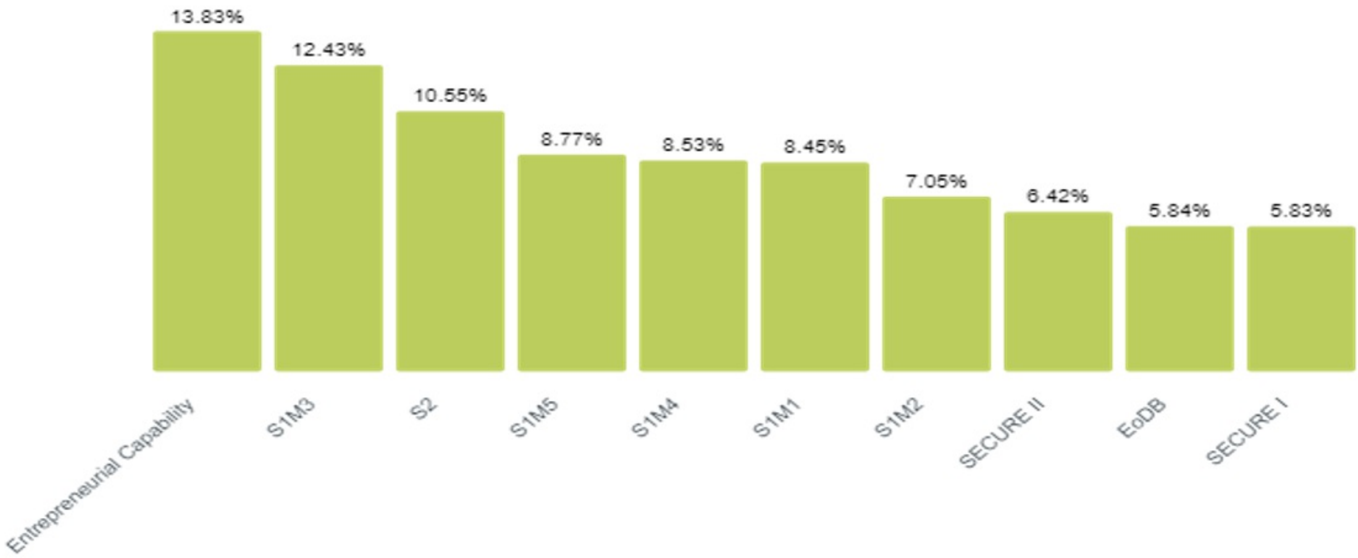

Figure 7. Model summary indicated by Deep Neural Networks

The Python Snippets in **APPENDIX II** represent the complexity and hidden layers indicating decision-making based on Predictor for Financial Metrics in a complex environment driven by numerous Nested loops. Further, to understand the performance of ANN (Unsupervised), the same has been compared with another model built using Decision Tree. The complexity of the Neural network and its hidden layers can be highlighted because - unlike other predictive models - its prediction is not solely driven by the Ease of Doing Business index (EoDB=5.84%). Further, to understand the performance of ANN (Unsupervised learning), its measures have been compared with another model built using Decision Tree (Supervised learning).

Decision Tree (DT) can be used in classification models and regression models. When the label/dataset is numerical, the decision tree can be applied in the latter models, while the attributive/categorical dataset type is used in the former models. Regression trees are used in regression analysis when the nature of the data set is non-linear.

Table 3. Comparison of Performance measure of both Decision Tree & Neural networks

Measure	DT	ANN	Measure	DT	ANN
Accuracy	77.00%	81.00%	*% Positive instances*	12.00%	9.00%
F-measure	0.08	0.1364	*Lift*	64.10%	128.20%
Precision	8.30%	16.70%	*K-S statistic*	3.40%	10.90%
Recall	7.70%	11.50%	*Kendall's Tau*	-0.0207	-0.0069
Phi coefficient	-0.0512	0.0343	*Spearman's Rho*	-0.0239	-0.0083
FPR	12.60%	8.60%			

Table 3 indicates a significant rise in the Accuracy, Precision, and Recall values as compared to a Supervised (Decision

Tree) model. The Unsupervised model built via Deep Learning outperforms the Supervised model in all the measures. As per Puth et al. (2015), Kendall's tau and Spearman's rho are accepted measures of non-parametric rank correlations where the coefficient assess where Spearman's rho appears to be higher, indicating statistical associations based on the ranks of the data.

Part III – Ensemble Model

According to Susskind et al. (2021), Neuro-symbolic AI seeks to combine traditional rules-based AI approaches with modern deep learning techniques and has already demonstrated the capability to outperform deep learning models to obtain high accuracy with minimal training data. With AI research, we are slowly exploring and understanding the inherent limitations of pure deep learning approaches (Sarker et al., 2021). As noted by Garcez & Lamb (2020), current advances in Artificial Intelligence (AI) and Machine Learning (ML) have achieved unprecedented impact across research communities and industries.

On the same lines resented research, Neuro Symbolic AI reflects Entrepreneurial Startup Evaluations in the form of ex-ante business model measures and location-dependent Ease of doing business. The indicators of Ease of Doing Business consist of Ease of starting a Business, dealing with Construction Permits, Getting Electricity, Registering Property, Getting Credit, Protecting Minority Investors, Paying Taxes, Trading across Borders, Enforcing Contracts, Resolving Insolvency, and further also reflect the overall ranking within the group (World Bank, 2019).

In consonance with IBM Research (2021), The Neuro-symbolic AI aims to develop a new paradigm to conceive a new methodology for AI that addresses the gaps remaining between today's state-of-the-art and the full goals of AI, while augmenting the strengths of statistical AI (machine learning) with the complementary capabilities of symbolic AI (knowledge and reasoning).

The above model in **Figure 8** is the closest representation of Neuro-symbolic AI that predicts the EAS considering the values of SECURE I and II.

It predicts EAS with 2 Hidden layers with a learning rate of 0.01 using minimal data. The ideal range of EAS calculated by the Neuro Symbolic AI is 112.85 to 167.19. It uses neural networks to recognize startup evaluation and a symbolic system to understand the macro environment and the causal relationships between them.

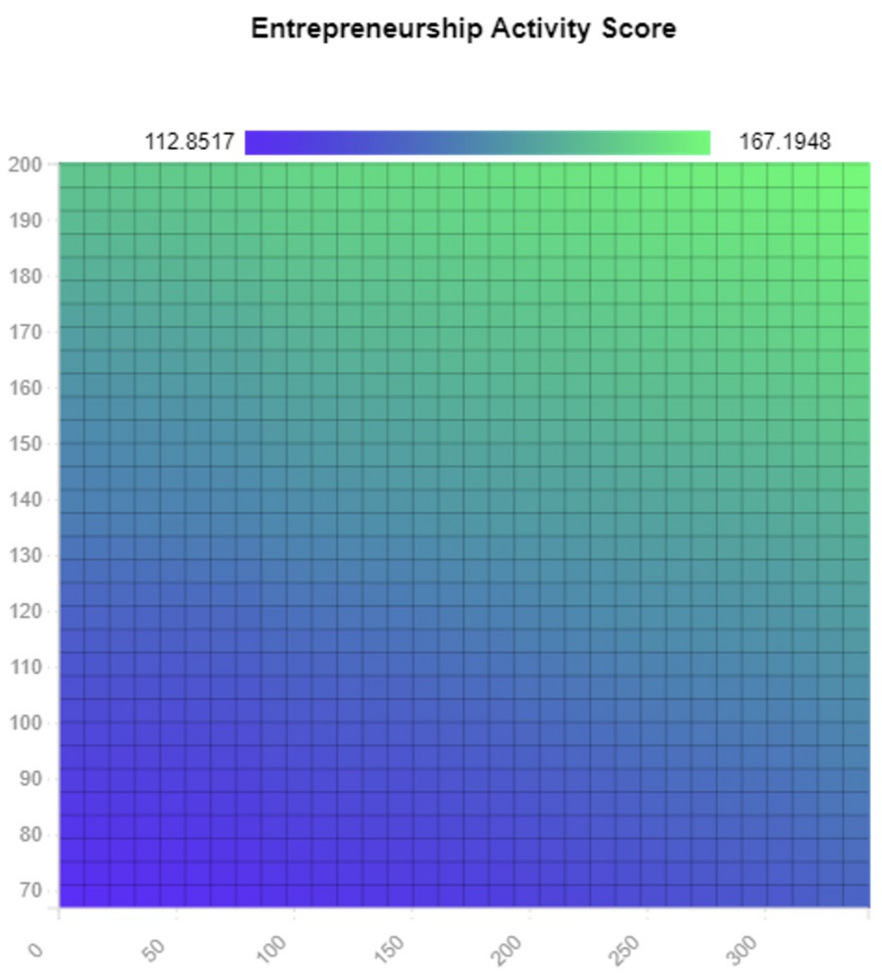

Figure 8. Neuro Symbolic AI indicating EAS

Performance measures of the above model indicate 1000% times improved performance compared to Mean & Random values offered by the null model (refer to **Figure 9**).

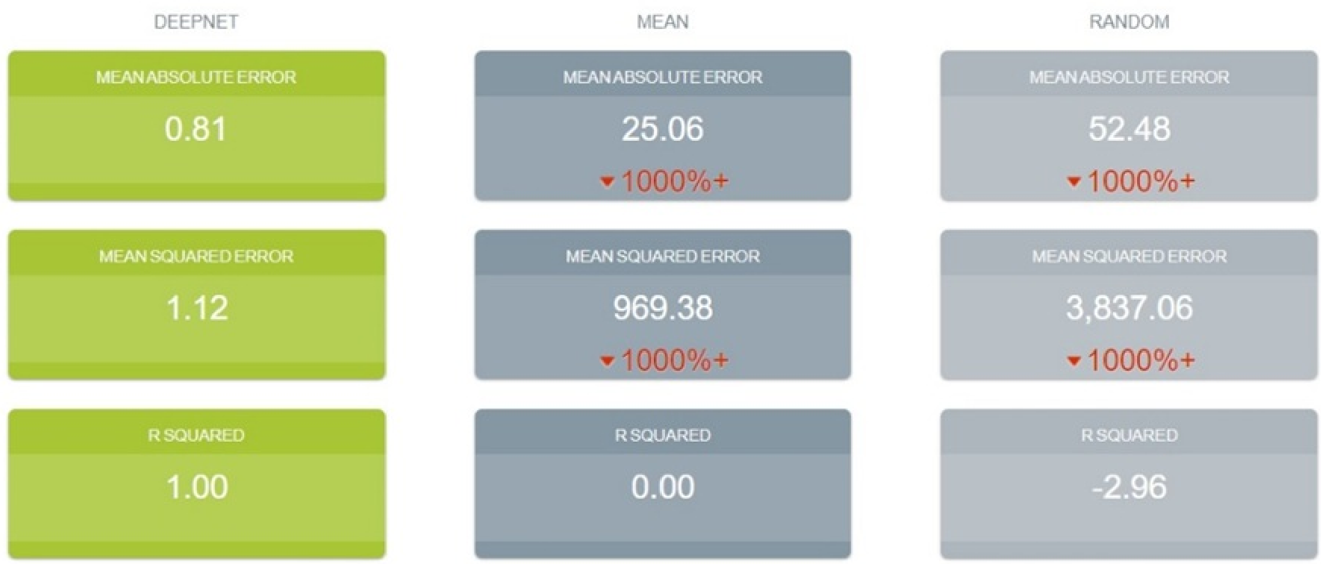

Figure 9. Performance measures of Neuro-symbolic AI

- **MAE: 0.81** (*As compared to 52.48 in the random model*)

Mean absolute error measures the difference between actual and predicted values in each data set. These values give us the absolute residual value, which determines how accurate or far are the predicted values from the actual values.

- **MSE: 1.12** (*As compared to 3837.06 in the random model*)

Mean squared error is a measure to calculate the error in the model. It is also known as mean square deviation, which means how much the data deviate from the regression line. When the distance between data points and the regression line is smaller, the model is considered reliable in predicting results. If the model produces a value equal to or less than zero, it will be considered a perfect model, which is highly unlikely.

- **R-Squared: 1.0 (***As compared to -2.96 in the random model*)

R-squared measure gives the value of change/variation in the dependent variable caused by the independent variable. It is known as the coefficient of determination, which measures the strength and effect of the relationship between dependent and independent variables. A higher R-square value represents the percentage of variability in the dependent variable, but it does not indicate that the model is good. To check the effectiveness of the regression model, other goodness of fit measures should be consulted.

The significant Field importance of the above model displayed by Neuro-symbolic AI can be seen from**APPENDIX III** where values of SECURE I (0.1173), RANK WITHIN GROUP (0.09736), SECURE II (0.08479) play an important role.

Reliability and Validity

The present use of machine learning in healthcare highlights the importance of defining model reliability. Following (Gilpin et al., 2019), evaluating the reliability and validity of machine learning models is crucial. Reliability refers to the consistency and stability of the model's predictions over time, while validity is the extent to which the model accurately represents the phenomenon being modeled (Mohajan, 2017).

One way to assess reliability is by using cross-validation techniques to evaluate the model's performance on different subsets of the data. This helps to ensure that the model is not overfitting to the specific data used to train it and is more likely to generalize well to new data (Nicora et al., 2022). Additionally, ensemble techniques, such as bagging or boosting, can help increase the model's reliability by combining multiple models into a single prediction.

For a model to be valid, it must accurately represent the phenomenon being modeled in the data used for training and testing. This can be done by carefully selecting the data sources and cleaning and preprocessing the data to remove any biases or errors (Boateng et al., 2018). Additionally, it is crucial to consider the interpretability of the model and whether the relationships it identifies are plausible and make sense in the context of the problem being studied.

As the basis of the research process, statistical validity and reliability are crucial to the study's success (Bagozzi & Yi, 2012; Hair et al., 2010). Statistical analysis without reliable and valid data can generate inaccurate or misleading conclusions, undermining the study's usefulness (Hair et al., 2014). Sarker (2021) believes that it is crucial to carefully evaluate the reliability and validity of machine learning models to ensure that they are valuable and accurate tools for solving real-world problems.

The same can be assessed based on the performance measures (MEAN ABSOLUTE ERROR, MEAN SQUARED ERROR, R-SQUARED VALUE) displayed by Neuro Symbolic AI, as shown in **Figure 9.**

Observations

Marketability, Viability. Feasibility, Desirability & Scalability assess the effectiveness of ex-ante measures of a business model. Its effect on ex-post performance measures can be observed in the Competence, Flexible entrepreneurial ecosystem. It also includes financial metrics such as Startup valuation, Sales growth, Profits & Market share. A novice entrepreneur can use AI to build predictive models that utilize Machine Learning and, with Logistic Regression analysis, reflect on Entrepreneurial Capability in four classes (Excellent/Good/Satisfactory/Poor). It can be seen from the considerably high Accuracy, Precision & Recall of an ML model.

The logistic regression indicates that only a 10% probability exists that Entrepreneurial capability would reach the ‘Excellent’ level.

Through unsupervised learning, Artificial Neural Networks can process data to predict Business Models’ ex-post measures (more specifically desired financial outcomes). It attempts to mimic the human brain through data inputs, weights, and biases. These elements work together complexly with multiple input/output /hidden layers. The Hidden layers consist of multiple interconnected nodes, each building upon the previous layer to refine and optimize the prediction or categorization. The results can efficiently recognize, classify, and describe objects within the data. When compared to other supervised models, it significantly reduces data uncertainty to make predictions. The same is seen from comparing performance measures when ANN possesses enhanced Accuracy, precision & Recall values achieved through Deep Learning.

The neural network indicates that even with a high SECURE I score, there is a probability of ‘Poor’ Financial performance, reflecting the importance of external factors that a startup may be subjected to.

Neuro Symbolic AI possesses both Statistical and Symbolic components that can be processed using the Analytical capabilities of AI to help eliminate data uncertainty while launching a startup. This process uses limited data and can improve confidence in entrepreneurial decision-making. The same is evident from exponentially improved model performance with minimal values represented by Mean Absolute and Squared Error.

The NSAI indicates the entanglement of ex-ante business model measures & ex-post measures of performance with Ease of doing business based on a location predicted using its correlation-ship using the Partial Dependance Plot.

Using the hybrid mechanism, NSAI would utilize a knowledge base and symbolic representations to respond. In the process, it could perceive the world and understand natural phenomena. Thus, integrating human knowledge into machine learning can significantly reduce data requirements and build explainable machine learning systems. Furthermore, this could further facilitate the interaction between human beings and machine learning systems.

Findings

Figure 10 compares evaluations done for the supervised (Decision Tree) and Deep Learning (Neuro Symbolic AI) models. The NSAI model, with its superior predictive capabilities, offers a robust outcome, as identified by Honda (2022).

Figure 10. Performance evaluation of Neuro Symbolic AI

This study indicates how the skill of an entrepreneur (in terms of ex-ante measures), along with the reflections from the real world (in terms of ex-post measures), can be used to predict the outcomes of the real world. With its greater accuracy and precision Neuro Symbolic AI can eliminate data uncertainty and improve confidence in entrepreneurial decisions to launch startups. A neuro-symbolic AI leverages logic and language (or symbols) with fewer data by using neural networks to create the knowledge base concerning the presented study. This approach provides a higher accuracy to entrepreneurs in evaluating their business models. It is expected to help reduce machine bias by making the decision-making process more transparent and explainable. By greater interpretability, new venture installs improved confidence to capture greater market valuations.

With its hybrid mechanism, neuro-symbolic AI leverages can fulfill more complex tasks and capture compositionality, causality, and complex correlations. That reflects enhanced data efficiency while pre-empting the market risks associated with the external business environment.

Discussions

Entrepreneurship is risky, and novice entrepreneurs often face significant challenges in creating and running a successful startup. The traditional approach to developing a business model framework can be complex and time-consuming, and inexperienced entrepreneurs may find navigating the numerous variables involved in the process challenging. However, recent advancements in artificial intelligence (AI) and machine learning have provided a new avenue for entrepreneurs to develop a more accurate and efficient business model framework. This research discusses the value of an AI-operated business model framework for novice entrepreneurs and considers the factors that should be considered to develop such a framework.

One significant advantage of an AI-operated business model framework is that it allows novice entrepreneurs to develop a comprehensive and customized framework based on their specific business needs. Data like market trends, consumer behavior, and industry insights can be analyzed by AI algorithms, which can provide valuable insights for developing a successful business model. It can further enhance accuracy and reliability by learning and adapting to changing market conditions based on the market's location.

An AI-driven business model framework must consider several factors to be successful. Data used to train the AI model must be relevant and representative of the market to establish its reliability and validity. Also, there is a need for the framework to incorporate multiple factors that affect a startup's success, such as financial projections, resource allocation, and strategic planning. Moreover, novice entrepreneurs should be able to interpret the model's results without requiring a technical background since the framework should be simple to use and understand.

Developing a framework for AI-controlled business models can potentially revolutionize the traditional approach to entrepreneurship. However, the framework's accuracy and reliability depend on the quality and relevance of the data used to train the AI model. Additionally, the framework should incorporate a range of variables that affect a startup's success and be designed to be user-friendly for novice entrepreneurs. By considering these factors, entrepreneurs can develop a practical AI-operated business model framework that can enhance their chances of creating a successful startup.

Inference

The presented research discusses using Artificial Intelligence (AI) to assess the desirability, feasibility, and viability of business models designed by novice entrepreneurs. The proposed SECURE II framework integrates Symbolic AI and Neural AI to aid entrepreneurial decision-making in launching startups. The framework compensates for the limitations of human cognition by enhancing the cognitive capacity for decision-making. The study also highlights the role of data science in advancing conventional social science research in three major areas: generating fresh insights, increasing the reproducibility of social research, and improving the triangulation of theory. The proposed research uses a non-traditional method to fulfill the objectives by utilizing AI to reduce data uncertainty and improve the robustness of ex-ante measures of business model design.

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Data availability: Data can be made available upon request due to privacy concerns.

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Appendices

Appendix I: Confusion matrix predicting 'Entrepreneurial Capability' via Logistic Regression

ACTUAL VS. PREDICTED						
	Excellent	**Good**	**Poor**	**Satisfactory**	**ACTUAL**	**RECALL**
Excellent	12	11	0	0	23	**52.17%**
Good	1	51	0	11	63	**80.95%**
Poor	0	0	5	16	21	**23.81%**
Satisfactory	0	2	0	91	93	**97.85%**
PREDICTED	13	64	5	118	200	**63.70%**
PRECISION	**92.31%**	**79.69%**	**100.00%**	**77.12%**	**87.28%**	**79.50%**

Appendix II: The Python Snippets for Deep Learning

```
def predict_financial_metrics(data={}):
    """ Predictor for Financial Metrics from model/6215d4a2aba2df062d0000ee

        Predictive model
    """
    if (data.get('s1m1') is None):
        return u'Satisfactory'
    if (data['s1m1'] > 20):
        if (data['s1m1'] > 23):
            if (data.get('entrepreneurship_activity_score') is None):
                return u'Satisfactory'
            if (data['entrepreneurship_activity_score'] > 109.90625):
                if (data.get('s1m3') is None):
                    return u'Satisfactory'
                if (data['s1m3'] > 16):
                    if (data.get('s1m2') is None):
                        return u'Satisfactory'
                    if (data['s1m2'] > 20):
                        if (data['s1m1'] > 24):
                            if (data.get('s2') is None):
                                return u'Good'
                            if (data['s2'] > 31):
                                return u'Good'
                            if (data['s2'] <= 31):
                                return u'Satisfactory'
                        if (data['s1m1'] <= 24):
                            if (data['s1m2'] > 22):
                                return u'Poor'
                            if (data['s1m2'] <= 22):
                                return u'Good'
                    if (data['s1m2'] <= 20):
                        if (data.get('s1m5') is None):
                            return u'Satisfactory'
                        if (data['s1m5'] > 36):
                            if (data['s1m2'] > 15):
                                return u'Satisfactory'
                            if (data['s1m2'] <= 15):
                                return u'Poor'
                        if (data['s1m5'] <= 36):
                            if (data.get('secure_ii') is None):
                                return u'Satisfactory'
                            if (data['secure_ii'] > 143.25):
{Redacted codes}
```

Appendix III: Field Importance displayed by Neuro-symbolic A.I.

Field	Importance
SECURE I	0.1173
RANK WITHIN GROUP	0.09736
SECURE II	0.08479
S2	0.07955
S1M5	0.07325
S1M2	0.04286
Resolving Insolvency	0.04261
Getting Credit	0.04261
Registering Property	0.04183
Paying Taxes	0.04001
S1M4	0.03917
S1M3	0.03796
S1M1	0.03794
Protecting Minority Investors	0.03631
Getting Electricity	0.03614
Trading across Borders	0.03499
Dealing with Construction Permits	0.03108
Enforcing Contracts	0.02996
Starting a Business	0.02578
Financial Metrics	0.01653
Entrepreneurial Capability	0.01047
ENTITY	0.00058

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