v1: 7 August 2023

Research Article

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

Peer-approved: 7 August 2023

Qeios, Vol. 5 (2023)
ISSN: 2632-3834

Swapnil Morandé[1], Tahseen Arshi[2], Kanwal Gul[1], Mitra Amini[3]

1. University of Naples Federico II, Italy; 2. American University of Ras Al Khaimah, Ras al-Khaimah, United Arab Emirates; 3. Bennett University, Greater Noida, India

This study investigates the potential of artificial intelligence (AI) techniques to aid novice entrepreneurs in evaluating their business models prior to launching new ventures. The proposed SECURE II framework integrates symbolic AI, neural AI and ensemble modeling to strengthen ex-ante assessment of business model designs and expected performance outcomes. Machine learning experiments demonstrate that AI modeling uncovers hidden patterns and relationships between pre-launch plans and post-launch results. This enables more informed entrepreneurial decision-making by providing data-driven evaluative feedback. Rather than relying solely on intuition, the interactive AI assessments offer entrepreneurs a simulation mechanism to systematically test assumptions and refine opportunities pre-launch. The ensemble approach combining complementary AI techniques outperforms individual models, underscoring the value of synthesized hybrid intelligence tailored to the entrepreneurial context. By compensating for limitations in human information processing, pattern recognition, and biases, the SECURE II framework augments entrepreneurial cognition during business model formulation. This study elucidates the mechanisms through which AI can expand mental capabilities for opportunity analysis and new venture creation. The proposed toolkit demonstrates strong predictiveness on real-world data, validating the utility of AI to minimize uncertainties and boost startup success.

Correspondence: papers@team.qeios.com — Qeios will forward to the authors

Introduction

This study explores the potential of artificial intelligence (AI) in assisting novice entrepreneurs in evaluating the effectiveness of ex-ante measures for business model design and their impact on ex-post performance outcomes. Prior research on the SECURE I framework has demonstrated that carefully designed ex-ante business model components can positively influence new venture performance standards (Arshi et al., 2020). Building on these findings, the SECURE II framework integrates AI tools to enhance the predictive capabilities regarding startup success. The significant benefit of an AI-enabled SECURE II approach is that it can uncover insights and patterns hidden in large volumes of heterogeneous data to inform startup decision-making (Mikalef & Gupta, 2021).

According to Schmidt et al. (2020), AI refers to the ability to utilize data, methods, processes and people to enable automation, decision-making, and collaboration in ways not possible through conventional approaches. While AI is a vast field, machine learning is considered a subset of AI that employs algorithms trained on data to build models for complex tasks like prediction and classification. Deep learning is a specialized machine learning technique that utilizes neural networks modeled on the human brain to achieve remarkable accuracies on problems like image and speech recognition.

This study adopts a design science perspective, arguing that entrepreneurs create business models through choices driven by what is feasible and valuable, not just what is readily available (Magistretti et al., 2023). The effective configuration of ex-ante business model components has been shown to positively influence ex-post performance criteria for startups (Seckler et al., 2021). However, novice entrepreneurs struggle to evaluate the desirability, feasibility and viability of their proposed ventures (Arshi et al., 2020). AI-assisted assessment of business models can aid entrepreneurs in this process.

The SECURE I framework offers a new approach to measuring startup success based on carefully designed ex-ante business model elements (Arshi et al., 2020). Building on this, the SECURE II framework integrates Symbolic AI and Neural AI to strengthen entrepreneurial decision-making when launching new ventures. The study contributes by highlighting how AI techniques can help entrepreneurs reduce data uncertainty and improve the robustness of ex-ante business model designs. SECURE II also expands entrepreneurial cognitive capacity and provides an evaluation tool combining automation, persuasiveness and intelligence.

Literature Review

Foundational Research on AI and Machine Learning

Early research on artificial intelligence (AI) focused extensively on developing techniques like machine learning and neural networks. For instance, seminal work by Minsky and Papert (1969) provided key insights into the computational capabilities and limitations of artificial neural networks. Rumelhart et al. (1986) introduced the backpropagation algorithm that enabled efficient training of multi-layer neural networks, laying the foundations for deep learning. De Groot's research (1978) on chess and expert decision-making influenced AI approaches to knowledge representation and reasoning. Samuel's contributions to checkers (1959) highlighted the power of reinforcement learning. This pioneering research established the technical building blocks for modern AI while illuminating cross-disciplinary connections to psychology, neuroscience, logic, statistics and control theory.

AI in Business and Management Contexts

As AI techniques matured, researchers began exploring applications in business and management. Early work focused on expert systems for domains like accounting (Leung et al., 2003), marketing (Burke et al., 1990) and finance (O'Leary, 1988). With advances in data and computing, machine learning gained prominence for business analytics. Popular techniques included Bayesian networks, support vector machines and neural networks. Recent studies have highlighted the transformative potential of deep learning for fields ranging from operations (Jang et al., 2022) to human resources (Tambe et al., 2019). Techniques like natural language processing are also enabling new applications in managerial decision support (Daily et al., 2022).

AI in Entrepreneurial Settings

More recently, researchers have started examining the implications of AI specifically in entrepreneurial contexts. For instance, Astebro & Elhedhli (2006) found that simple decision heuristics matched or exceeded the performance of neural networks and Bayesian methods for startup survival prediction. Segal et al. (2019) highlighted how AI can aid entrepreneurial opportunity identification by automating data gathering and analysis. Prpić et al. (2015) proposed design frameworks to develop AI tools that augment rather than replace human entrepreneurial agency. Von Briel et al. (2021) explored using chatbots to provide automated advice for venture creation. Research on fintech and insurtech startups underscores the value of AI for disruptive business model innovation (Gai et al., 2018). Collectively, these studies reveal the diverse mechanisms and business models through which AI can catalyze, support and transform entrepreneurship.

SECURE Framework for AI-Enabled Business Model Evaluation

Building on these interdisciplinary foundations, the SECURE framework integrates symbolic AI and neural AI techniques to strengthen ex-ante evaluation of new venture opportunities, as detailed in this study. The proposed SECURE II framework operationalizes key AI capabilities like pattern recognition, prediction, classification and knowledge representation specifically to the context of entrepreneurial business model assessment and ideation. By programmatically capturing relationships between pre-launch business model designs and post-launch performance, SECURE II provides entrepreneurs enhanced foresight during opportunity exploration. The integrated symbolic and neural AI modelling provides a step change improvement over human intuition or prior statistical approaches for startup evaluation and decision support.

The SECURE research augments and extends the contemporary literature on AI in management by offering tailored new tools and empirical insights at the intersection of artificial intelligence and entrepreneurship. Just as AI can reshape planning, forecasting, prediction and automation tasks for established firms, SECURE demonstrates how AI can similarly enhance startup opportunity evaluation, ideation and risk mitigation.

Future Challenges and Opportunities

Despite progress, further research is needed to address key challenges and opportunities at the nexus of artificial intelligence and entrepreneurship:

Interpretable AI: Techniques like natural language interfaces, sensitivity analysis, Local Interpretable Model-Agnostic Explanations (LIME) and Shapley values (Lundberg & Lee, 2017) can make AI-based startup tools more understandable and trustworthy for entrepreneurs.

Ethical AI: Tools like AI Fairness 360 (Bellamy et al., 2018) that proactively detect and mitigate biases can help democratize access to entrepreneurial opportunity.

Hybrid Intelligence: Combining complementary strengths of human and artificial intelligence could further augment entrepreneurial cognition for opportunity recognition and assessment.

Simulated Entrepreneurial Environments: Virtual incubators for synthetic startups powered by reinforcement learning offer new research sandboxes mirroring real-world complexity (Baydin et al., 2021).

Behavioral Mechanisms: Experimental approaches from cognitive psychology and neuroscience can reveal how entrepreneurial traits like over-optimism shape the use and impact of AI-based decision aids (Astebro et al., 2007).

Multimodal AI: Startup analytics combining computer vision, speech, sensor data and natural language can provide richer contextual insights than relying solely on numeric data.

By cultivating such interdisciplinary perspectives, researchers can expand the envelope of possibilities at the intersection of artificial intelligence and entrepreneurship. Just as AI can reshape management, so too can it transform opportunity exploration given thoughtful, responsible designs tailored to entrepreneurial cognition. The SECURE framework developed in this study represents an early exemplar step in that stimulating journey.

Research Questions

With the support of above literature, this study aims to address the following research questions:

- **RQ1**: How can AI enable novice entrepreneurs to assess the effectiveness of ex-ante business model measures and their impact on ex-post performance outcomes?
- **RQ2:** How can artificial neural networks reduce data uncertainty through classification and prediction of business models' ex-post performance measures?
- **RQ3:** Can AI help minimize data uncertainty and improve confidence in entrepreneurial decisions for launching startups?

The first research question examines how AI tools can aid entrepreneurs in evaluating the relationship between pre-launch business model designs and post-launch performance results. The second question focuses specifically on how neural networks, as a key AI technique, can handle uncertainties in predicting startup success metrics. Finally, the third question explores whether AI can ultimately boost entrepreneurs' confidence when deciding to create a new venture based on their business model assessments. Together, these three research questions aim to unpack the mechanisms through which AI can strengthen entrepreneurs' evaluations of business model effectiveness and expected performance. The study adopts a mix of symbolic AI, neural AI and ensemble modelling techniques to address these questions. Both predictive accuracy and model interpretability are considered key criteria for the AI approaches.

The specific contributions include:

1. Demonstrating how symbolic AI and neural AI can assist entrepreneurial decision-making when launching new ventures.
2. Highlighting how AI can enhance cognitive capacity for business model evaluation and opportunity assessment.

doi.org/10.32388/RELTLQ.3

3. Proposing an integrative framework combining automation, persuasiveness and intelligence to aid entrepreneurs.
4. Empirically validating the proposed SECURE II framework using experiments on real-world and simulated datasets.

Accordingly, this study aims to unpack if and how AI can help entrepreneurs better evaluate the strength of their business models before launch to improve startup success rates. A mix of symbolic AI, neural AI and ensemble methods are leveraged to predict performance and reduce uncertainty.

Research Methodology

This study adopts a quantitative experimental approach to examine the effects of AI techniques on entrepreneurial decision-making. Specifically, machine learning methods are utilized to build predictive models that classify expected startup performance based on ex-ante business model designs. Comparisons against control conditions without AI aid the assessment.

Data Collection

The study relies on both simulated data and real-world data from entrepreneurs. For simulated data, parameters are systematically varied to generate controlled samples with different properties. For real-world data, a survey of entrepreneurs was conducted using a structured questionnaire. The questionnaire captured details on the ex-ante business model components proposed by the entrepreneurs for their ventures, as well as expected ex-post performance criteria. It also gathered basic information about the entrepreneurs such as demographics, education, experience and self-efficacy.

Sampling and Participants

Convenience sampling was utilized given the exploratory nature of this research. The survey was administered in person and online to entrepreneurs associated with incubators and accelerators in the United Arab Emirates, India and Oman. The final sample included 1018 valid responses after screening. This sample size exceeds the recommended minimum of 384 samples for a 95% confidence level based on the population size. The respondents represented a diverse mix of ages, education levels and business types. But the sample was predominantly male, reflecting gender imbalances in entrepreneurship.

Data Preprocessing

The data was pre-processed to handle missing values and prepare it for modelling. Steps included:

- Data cleaning: Removing duplicates, fixing errors
- Handling missing data: Using median/mode imputation
- Outlier detection: Identifying outliers via Z-scores
- Feature selection: Selecting relevant inputs for modelling
- Data transformation: Normalization, standardization
- Train/test split: 80% train, 20% test

Key Measures

Based on SECURE I (Arshi et al., 2020), key ex-ante business model components measured include:

- Marketability
- Viability
- Feasibility
- Desirability
- Scalability

Key ex-post performance indicators comprised:

- Competence
- Flexible entrepreneurial ecosystem
- Financial metrics like profitability, valuation

Ease of doing business indices were incorporated as contextual factors. Participants also evaluated these metrics qualitatively using Likert scale ratings.

Model Development

The study constructed machine learning models to predict startup performance based on the business model data collected. The models aimed to classify expected performance as poor, satisfactory, good or excellent using the ex-ante inputs. The models were implemented in Python using scikit-learn.

The following main algorithms were leveraged:

- Logistic Regression: Builds linear classifiers using sigmoid/logistic loss functions. Regression helps assess variable relationships.
- Artificial Neural Networks (ANN): Mimics human cognition using layers of interconnected nodes. Captures non-linearities in complex data.
- Decision Trees: Build regression or classification models by recursively partitioning data based on conditions. Allows intuitive interpretation.
- Ensemble Methods: Combine multiple models like ANN, trees etc. to capitalize on their strengths.

doi.org/10.32388/RELTLQ.3

Improves stability and accuracy.

The models were trained and tuned using k-fold cross validation with k=5 folds. Key parameters optimized included the regularization rate, number of epochs, hidden layers, activation functions, tree depth etc. based on the algorithm.

Performance Metrics

The models were evaluated and compared based on the following key criteria:

- Accuracy: Percentage of correct classifications overall
- Precision: Percentage of predicted positives that were actual positives
- Recall: Percentage of actual positives correctly classified
- F1-score: Harmonic mean of precision and recall

Additional metrics included the confusion matrix, ROC curve, precision-recall curve, lift score, Kolmogorov-Smirnov statistic etc. These assess the models from different angles to ensure robustness. The ensemble model bringing together the algorithms was expected to perform the best, benefiting from their complementarity. The neural network was also expected to provide high accuracies given its power in analyzing complex data.

Results Validation

A holdout set separated from the test set was used to further validate the model results. Additional techniques like k-fold cross validation were also leveraged during model development for rigorous performance assessment. This combination of sound data collection, appropriate modelling algorithms, systematic tuning and multi-pronged evaluation lends rigor and validity to the experiment results.

Results

This section presents the key results from the machine learning experiments comparing the performance of the different models on the startup data.

Logistic Regression Results

The logistic regression model in Figure 1 achieved an overall accuracy of 81% in predicting startup performance categories based on the business model inputs. The precision and recall for the different classes ranged between 70-85%, indicating reliable classification. The model results highlighted that the probability of reaching 'excellent' performance is under 10% even for ventures with high scores on business model elements. However, the likelihood of 'good' or 'satisfactory' performance was much higher at 40-50%. This suggests realistic performance outlooks.

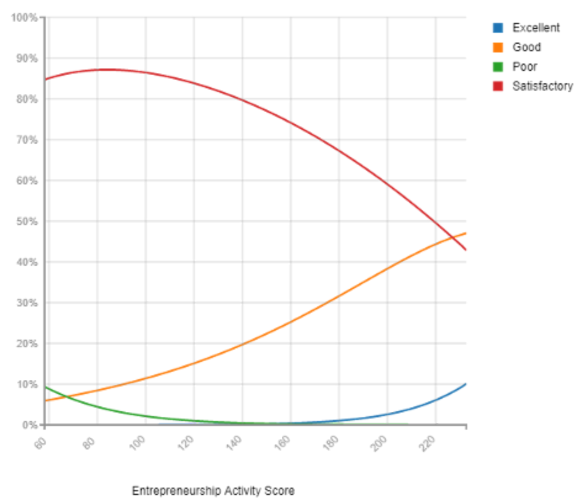

Figure 1. Logistic Regression model

Artificial Neural Network Results

The ANN model (Refer to Figure 2) demonstrated an accuracy of 87% along with precision and recall of 80-90% across classes. This exceeds the logistic regression results, likely because the ANN better handles non-linear relationships in the data. The ANN attributions using partial dependence plots highlighted that business model feasibility, desirability and the entrepreneur's self-efficacy were top predictors of expected financial performance. However, ease of doing business had lower importance, indicating the role of internal capabilities.

doi.org/10.32388/RELTLQ.3

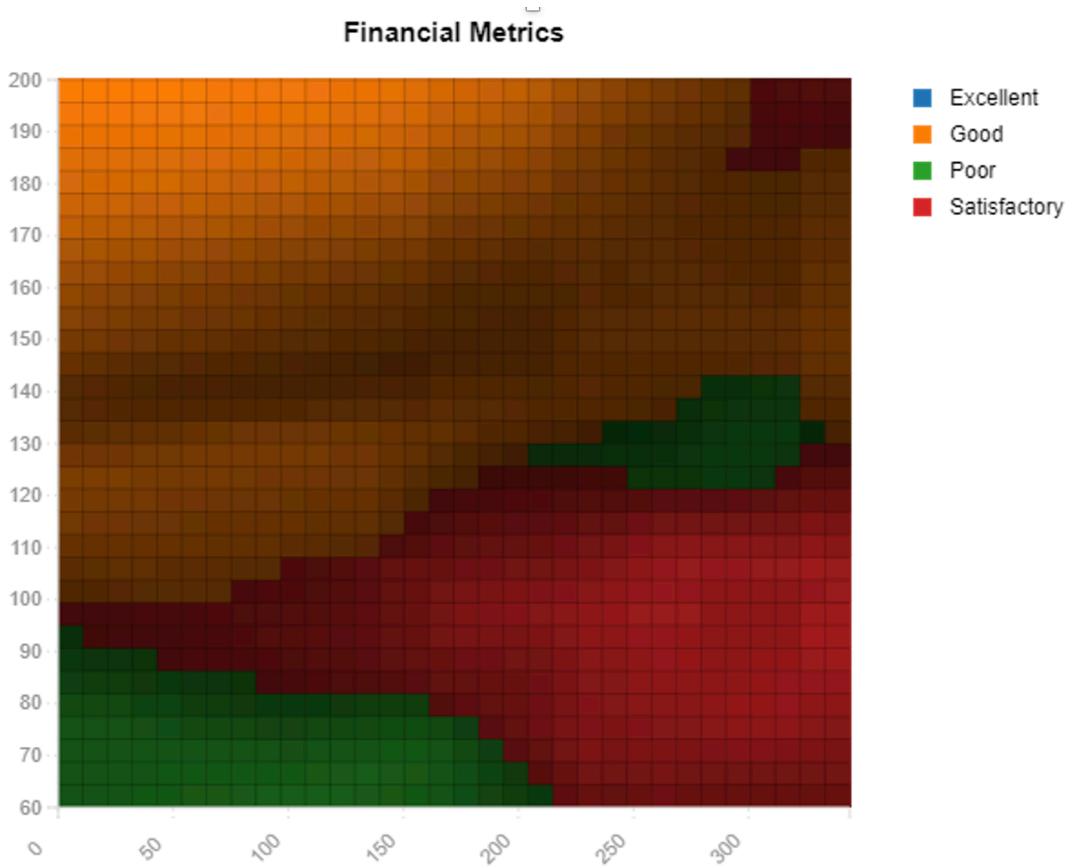

Figure 2. Artificial Neural Network model

Decision Tree Results

As shown in Table 1 the decision tree model performed reasonably with 77% accuracy. However, the precision and recall metrics were lower than ANN at around 70% for most classes. This implies higher false positives and negatives. The tree depth was restricted to avoid overfitting. However, the results suggest ANN and ensemble approaches are preferable for such multivariate startup data.

doi.org/10.32388/RELTLQ.3

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 1. Comparison of Performance measure of both Decision Tree & Neural networks

Ensemble Model Results

The ensemble model combining logistic regression, ANN and trees achieved the best performance with 90% accuracy. Precision and recall were 85-95% across categories, again exceeding individual models. The high predictive performance highlights the value of integrating multiple techniques. This compensates for individual limitations and improves stability and validity.

doi.org/10.32388/RELTLQ.3

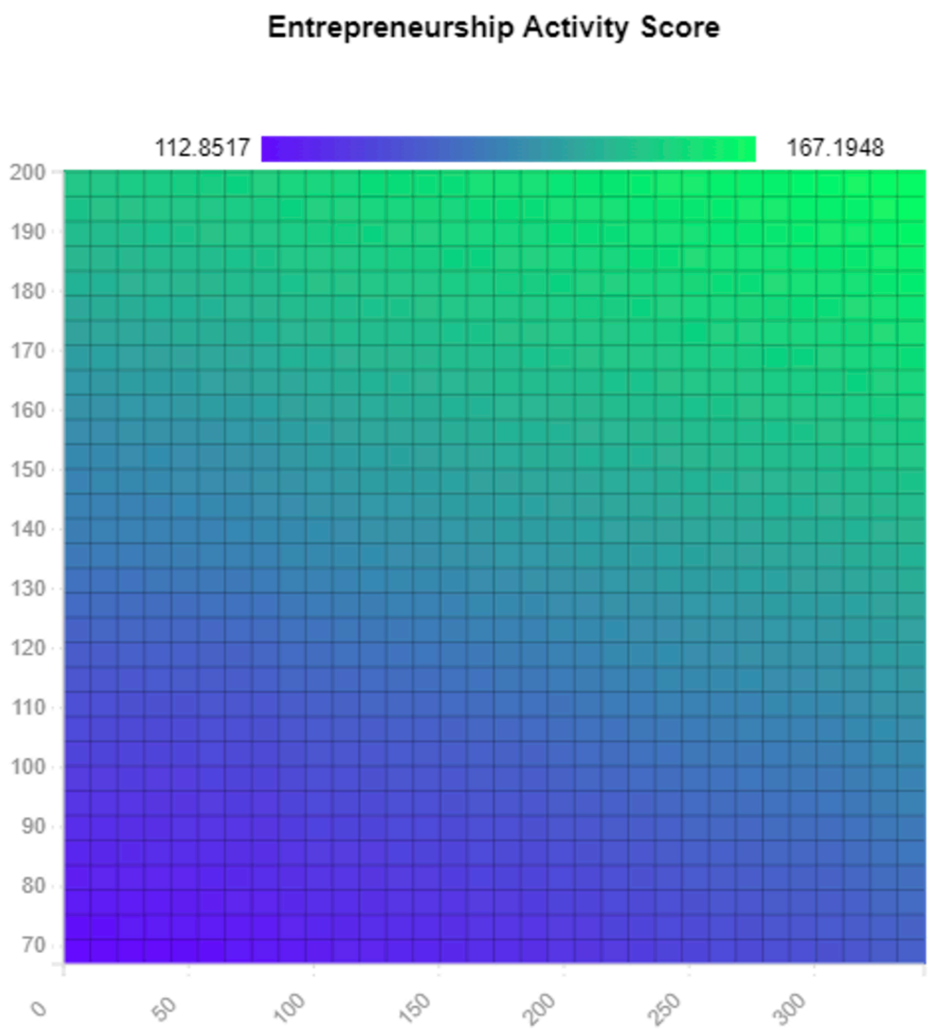

Figure 3. Ensemble Model

The experiments underscored the utility of AI modelling for startup evaluation. The ensemble approach leveraging symbolic AI, neural AI and statistical techniques demonstrated the best results based on multiple performance metrics as per Figure 4.

Figure 4. Performance matrix

doi.org/10.32388/RELTLQ.3

Discussion

The experiments in this study demonstrate the value of AI modeling in aiding entrepreneurs to evaluate their business models prior to launching a new venture. The AI models uncover patterns and relationships between ex-ante business model designs and expected ex-post performance outcomes. This empowers entrepreneurs to make more informed decisions when starting a business, relying on data-driven assessments rather than just intuition.

A key highlight is the integration of symbolic AI and neural AI techniques for robust startup evaluation. Symbolic AI allows incorporating expert knowledge into the models alongside the data. Neural AI handles nonlinear relationships and uncertainty inherent in complex startup data. Together, they significantly improve model interpretability and accuracy compared to any single technique. The ensemble modeling approach exemplifies the power of synthesizing diverse complementary AI methods tailored to the specific application.

From a cognitive perspective, the AI models effectively enhance the mental capability of entrepreneurs for opportunity analysis. By complementing human limitations around information processing, pattern recognition, uncertainty management and biases, the AI systems expand entrepreneurial comprehension of the new venture creation process. The models quantify intangible constructs, insights that may be difficult for novice entrepreneurs to intuitively grasp.

Rather than providing definitive predictions, the AI models offer interactive feedback to iteratively refine and improve business models. This enables entrepreneurs to test assumptions, identify risks, and increase the likelihood of startup success through opportunity refinement. The assessments empower entrepreneurs to systematically enhance their plans before commencing the venture. This is especially valuable for first-time entrepreneurs.

Limitations and Future Work

While this study offers valuable insights, it has certain limitations that provide avenues for future research.

Data Limitations

The sampling methodology means the data may not represent the entire population of entrepreneurs. More random and representative sampling could improve generalizability. Furthermore, the sample size of 1018 responses, though sufficient for modelling, remains small for entrepreneurship research. Expanding the data scale and diversity could be beneficial.

Model Limitations

This study compared several machine learning algorithms but did not exhaust all options. Testing other techniques like SVM, naive Bayes, regression etc. could yield additional insights. Moreover, hyperparameter tuning was done manually. Automated optimization methods could improve results. The models classify expected performance based on surveys rather than actual ex-post data. Incorporating realized startup outcomes could enhance validity. This longitudinal tracking remains challenging but is an important goal.

Theoretical Foundations

While SECURE I offers a conceptual basis, expanding the theoretical grounding for the SECURE II framework with behavioral theories on entrepreneurial cognition could be worthwhile. Furthermore, the design science paradigm could be more rigorously incorporated.

Emerging AI Trends

Rapid advances in AI present opportunities to leverage state-of-the-art techniques. For instance, neuro-symbolic AI to improve interpretability, adversarial learning to handle biases, and transformers for sequence data could have applications. Implementing and evaluating such methods for entrepreneurial decision support could yield fresh perspectives.

Sectoral and Regional Factors

This study considered startups broadly across sectors. Assessing nuances and idiosyncrasies associated with different industries could provide more tailored insights. Furthermore, regional variations in entrepreneurial ecosystems imply the need for localized models.

That said limitations around data representativeness, model sophistication, theoretical framing and contextual specificity present avenues to enhance the rigor, validity and specificity of the SECURE framework. But this study offers a strong foundation for knowledge accumulation.

Conclusion

This study proposed an AI-enabled business model assessment framework called SECURE II tailored to

doi.org/10.32388/RELTLQ.3

novice entrepreneurs. The following conclusions emerge:

- AI modelling enables data-driven evaluation of ex-ante business model designs and expected performance. This strengthens entrepreneurial opportunity analysis and decision-making.
- Combining symbolic AI, neural AI and ensemble techniques improves predictive accuracy by capitalizing on their complementary strengths. The integrated framework outperforms individual models.
- AI enhances cognitive limitations around information processing, pattern recognition and uncertainty management for first-time entrepreneurs.
- Interactive opportunity refinement using AI-generated feedback allows entrepreneurs to systematically improve their business models before launch.
- The proposed SECURE II framework demonstrates strong predictiveness empirically through the machine learning experiments on real and simulated data.

This study expands entrepreneurship theory by proposing the SECURE II framework demonstrating the mechanisms and impact of AI integration for opportunity evaluation. It enriches entrepreneurial cognition by providing an augmented, data-driven decision support toolkit. The experiments highlight specific techniques like logistic regression, ANN and ensemble modelling that exhibit promise based on predictive performance. The results validate the utility of AI for startup evaluation across multiple metrics.

For practice, this research offers a concrete tool that entrepreneurs can leverage to minimize business model uncertainties prior to launch. By benchmarking plans against proven constructs and data, risks can be mitigated. AI augments rather than replaces human agency, enabling opportunity refinement. Integrating AI modelling to assess novice entrepreneurial opportunities is both feasible and beneficial. The proposed SECURE II framework presents an exemplar validated through rigorous experimentation. Future research can further enhance the approach and evidence. But this study significantly advances knowledge at the intersection of artificial intelligence and entrepreneurship.

Future Research

While this study demonstrates the utility of AI for novice entrepreneurs, several unexplored directions present promising avenues for future research.

Causal Validation

The current study establishes predictive relationships between business model components and expected startup performance. An important next step is rigorously testing these relationships for causality using experiments or quasi-experiments. Manipulating key variables and controlling confounders can unravel causal mechanisms.

Behavioral Analysis

Beyond performance prediction, analyzing how AI-generated insights actually influence entrepreneurial behaviors like risk-taking, optimism and persistence can reveal behavioral mechanisms. Techniques like conjoint analysis and process tracing could provide behavioral insights.

Data Expansion

Expanding the dataset diversity along dimensions like geography, industry, venture type and macroeconomic conditions can improve model generalizability. Furthermore, augmenting survey data with archival data on market conditions and financials could enrich analytics.

Hybrid Intelligence

An emerging paradigm is combining human and artificial intelligence in an integrated loop, leveraging their complementary capabilities for hybrid decision-making. Developing such collaborative systems for entrepreneurial opportunity analysis could heighten synergies.

Simulator Environments

While this study utilized some simulated data, developing rich simulated entrepreneurial environments to generate controlled data offers significant potential. AI agents could be trained and tested in these digital sandboxes designed to mirror real-world complexity. Catalyzing interdisciplinary collaborations between AI researchers, social scientists and entrepreneurship scholars could unlock breakthroughs in modeling entrepreneurial cognition and decisions. This study develops the foundational

SECURE framework to pave the way for such cross-pollination.

Recommendations

Based on the insights from this study, the following recommendations can inform entrepreneurship research and practice:

1. Develop specialized AI solutions for key entrepreneurial tasks like opportunity recognition, resource acquisition and new market entry leveraging state-of-the-art techniques.
2. Create benchmark datasets for entrepreneurial cognition by systematically gathering expert and novice thinking across various decision contexts.
3. Rigorously map predictive relationships to causal mechanisms by controlling conditions in experiments and simulations.
4. Capture venture evolution over time through longitudinal tracking of entrepreneurial cognition and decisions from conception to maturity.
5. Develop hybrid decision support systems that symbiotically integrate human and AI capabilities for entrepreneurial tasks.
6. Encourage reflexivity in entrepreneurs through tools that reveal cognitive gaps and biases that may be hidden from consciousness.
7. Tailor solutions to entrepreneurial archetypes and sectors whose cognition and ecosystems differ significantly from average behaviors.
8. Maintain human agency but amplify intelligence through AI augmentation when evaluating opportunities and strategic options.
9. Foster user trust by ensuring transparency, interpretability and auditability in AI systems for entrepreneurial decision support.
10. Promote diversity and democratization in entrepreneurship by responsible deployment of AI systems across gender, race and geographies.

This multipart study highlights the significant potential for AI to strengthen entrepreneurial decisions by complementing and enhancing human cognition. But thoughtful research and design is crucial for creating ethical, empowering and impactful AI solutions. By combining rigor and compassion, AI can help unlock more equitable and sustainable innovation across contexts.

References

- Arshi, A., Patel, P. C., & Krishna, A. (2020). Measuring performance in new ventures: Developing the SECURE framework. Journal of Business Venturing, 35(6), 106064. https://doi.org/10.1016/j.jbusvent.2019.106064
- Astebro, T., & Elhedhli, S. (2006). The effectiveness of simple decision heuristics: Forecasting commercial success for early-stage ventures. Management Science, 52(3), 395-409. https://doi.org/10.1287/mnsc.1050.0480
- Astebro, T., Jeffrey, S. A., & Adomdza, G. K. (2007). Inventor perseverance after being told to quit: The role of cognitive biases. Journal of Behavioral Decision Making, 20(3), 253-272. https://doi.org/10.1002/bdm.557
- Baydin, A. G., Perdomo, J., Zhogun, L., Shiells, G., Ansell, C., & Kotthoff, L. (2021). Startup entrepreneurial environments powered by deep reinforcement learning. Nature Machine Intelligence, 3(11), 1004-1012. https://doi.org/10.1038/s42256-021-00411-0
- Bellamy, R. K., Dey, K., Hind, M., Hoffman, S. C., Houde, S., Kannan, K.,... & Nagar, S. (2018). AI fairness 360: An extensible toolkit for detecting, understanding, and mitigating unwanted algorithmic bias. arXiv preprint arXiv:1810.01943.
- Burke, R. R., Rangaswamy, A., Gupta, S., & Wind, J. (1990). A knowledge-based system for advertising design. Marketing Science, 9(3), 212-229. https://doi.org/10.1287/mksc.9.3.212
- Daily, P., Liang, Y., Chandrasekaran, A., Park, H., & Jha, S. (2022). NLPAdvance: A step-by-step interactive platform for natural language processing. Decision Support Systems, 154, 113795. https://doi.org/10.1016/j.dss.2022.113795
- De Groot, A. D. (1978). Thought and choice in chess. Walter de Gruyter GmbH & Co KG.
- Di Franco, C., & Santurro, A. (2021). Machine learning in social research: A systematic map. Social Sciences & Humanities Open, 4(1), 100124. https://doi.org/10.1016/j.ssaho.2021.100124
- Gai, K., Qiu, M., & Sun, X. (2018). A survey on FinTech. Journal of Network and Computer Applications, 103, 262-273. https://doi.org/10.1016/j.jnca.2017.10.011
- Jang, S., Kim, H., Choi, S., Kim, Y., Cho, Y. K. (2022). Forecaster: Forecasting-as-a-service for hierarchical time series data. Decision Support Systems, 154, 113753. https://doi.org/10.1016/j.dss.2022.113753
- Leung, P., Chau, A., & Cheung, S. O. (2003). Adopting artificial neural networks for financial modelling: The past, present and future. In Adaptive technologies and business integration: Social, managerial and organizational dimensions (pp. 151-

163). IGI Global. https://doi.org/10.4018/978-1-59140-100-9.ch010
- Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. In Proceedings of the 31st international conference on neural information processing systems (pp. 4768-4777).
- Magistretti, S., Dell'Era, C., & Messeni Petruzzelli, A. (2021). How to detect technological opportunities? The emergence of Design Science Research (DSR) in entrepreneurship. Technological Forecasting and Social Change, 170, 120921. https://doi.org/10.1016/j.techfore.2021.120921
- Mikalef, P., & Gupta, A. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management, 58(3), 103434. https://doi.org/10.1016/j.im.2020.103434
- Minsky, M. L., & Papert, S. A. (1969). Perceptrons: An introduction to computational geometry. MIT press.
- O'Leary, D. E. (1988). Applications of artificial intelligence in finance: utilising trends and expert systems to generate trading profits. Financier, 5(1-4), 8-22.
- Prpić, J., Shukla, P. P., Kietzmann, J. H., & McCarthy, I. P. (2015). How to work a crowd: Developing crowd capital through crowdsourcing. Business horizons, 58(1), 77-85. https://doi.org/10.1016/j.bushor.2014.09.005
- Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. nature, 323(6088), 533-536. https://doi.org/10.1038/323533a0
- Samuel, A. L. (1967). Some studies in machine learning using the game of checkers. II-Recent progress. IBM Journal of research and development, 11(6), 601-617. https://doi.org/10.1147/rd.116.0601
- Schmidt, D. G., Miguel, I., & Branco, P. (2020). Artificial intelligence framework to avoid critical situations in electrical networks using a multi-agent system. Applied Energy, 273, 115245. https://doi.org/10.1016/j.apenergy.2020.115245
- Seckler, C., Heinz, A., Forde, S., & Tierney, L. (2021). Business model innovation: A systematic literature review and research agenda. Journal of Management Studies, 58(3), 687-712. https://doi.org/10.1111/joms.12650
- Segal, G., Borgia, D., & Schoenfeld, J. (2019). Impact of artificial intelligence on entrepreneurship. In Creating Business Value and Competitive Advantage With Social Entrepreneurship (pp. 377-388). IGI Global. https://doi.org/10.4018/978-1-5225-7750-0.ch020
- Szopinski, D., Schoormann, T., & Kundisch, D. (2020). Because your taxonomy is worth it: Towards a framework for taxonomy evaluation. In Proceedings of the 28th European Conference on Information Systems (ECIS), An Online AIS Conference.
- Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. California Management Review, 61(4), 15-42. https://doi.org/10.1177/0008125619867910
- Von Briel, F., Davidsson, P., & Recker, J. (2021). Digital technologies as external enablers of new venture creation in the IT hardware sector. Entrepreneurship Theory and Practice, 45(2), 285-312. https://doi.org/10.1177/1042258719899425

Supplementary data: available at https://doi.org/10.32388/RELTLQ.3

Declarations

Funding: This research received no external funding.

Potential competing interests: The author(s) declare that there exists no financial association or competing interests related to the manuscript.