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Research article

AI-driven insights into nascent entrepreneurship: exploring the role of inclusive entrepreneurial ecosystem factors

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Abstract: Entrepreneurship is a fundamental driver of economic growth, innovation, and sustainable development, and nascent entrepreneurial activity serves as a key indicator of economic dynamism. This study addresses critical gaps in the existing literature by leveraging advanced machine learning models embedded with mathematical equations (follow algorithms to achieve accuracy and predictability)—XGBoost, Random Forest, and Decision Tree—to predict total early-stage entrepreneurship levels based on inclusive ecosystem factors, including resources, governance, culture, and markets. While previous research has primarily relied on traditional statistical techniques to infer causality these methods are inherently limited in their ability to predict future trends due to their linear and static nature. By employing sophisticated machine learning algorithms, this study offers a novel approach to understand the complex and dynamic interactions between inclusive factors and entrepreneurial outcomes. Our findings highlight that Inclusive Resources are the most influential predictor across all models, followed by Inclusive Governance and Inclusive Markets, with Inclusive Culture playing a variable yet significant role. Among the models tested, Random Forest emerges as the most effective in predicting nascent entrepreneurship, achieving an optimal balance of accuracy, sensitivity, and specificity. These insights contribute to the academic discourse on entrepreneurship while offering practical implications for policymakers and practitioners that seek to foster sustainable

economic growth in alignment with the United Nations Sustainable Development Goals (SDGs). By integrating machine learning into the entrepreneurial ecosystem theoretical framework within inclusive context, this study provides decision-makers with more precise tools to foster and promote entrepreneurial activity, ultimately supporting the development of more inclusive and resilient economies.

Keywords: inclusive entrepreneurial ecosystem; machine learning; nascent entrepreneurship
Mathematics Subject Classification: 62P30, 68T05

1. Introduction

The role of sustainable growth considers as an important outcome for socioeconomic development. Considering this critical outcome, scholars and practitioners have been focusing on entrepreneurial development activities, which are considered as an important driving force for growth and sustainability. The effectiveness of entrepreneurial development is a critical indicator of socioeconomic progression [1]. For exponential growth, entrepreneurial development works as a critical tool that explores and exploits new business opportunities [2]. Scholars have mainly focused on the role of governance, alongside the economic and institutional context for entrepreneurial development activities [3,4]. Additionally, to achieve sustainable regional development, policy makers have focused on leveraging policies that favor higher level of entrepreneurial activities [5]. Over the last two decades, the entrepreneurial ecosystem (EE) has become a popular metaphor that focuses on holistic entrepreneurial context [6]. The EE refers to interconnected actors and factors that foster productive entrepreneurial development [7]. In the field of the EE, there is still a notable theoretical and research gap of predicting successful entrepreneurial outcomes and identifying underlying patterns rather than solely understanding causality. For instance, a garden needs diverse plants and conditions to thrive; similarly, entrepreneurial activities require supportive contextual conditions for entrepreneurial development. Recently, the EE perspective has been extended conceptualized, and operationalized as an inclusive entrepreneurial ecosystem (IEE) [8,9]. According to the sustainable development goals (SDGs), without involvement of all social groups, inclusive growth could not be achieved, which is considered an important outcome of socioeconomic progression [8,10]. In this regard, the participation of all actors without gender, social, and economic discrimination is necessary for inclusive growth [8]. In addition, inclusive factors cultivate and transform the EE, where all actors access equal opportunities to become successful entrepreneurs.

Previous studies have established the role of the EE towards socioeconomic progression along with certain limitations of inclusive growth. For instance, Danial Isenberg defined the EE as a complex system where the relationship between actors and factors leads to entrepreneurial development activities [11]. To an extent, all stakeholders (Industry, institutions, and policymakers) have acknowledged the role of the EE towards socioeconomic development [12]. However, the equal participation of all communities is significant to foster entrepreneurial activities that necessitate to align with SDGs. The inclusion of marginalized communities (ethnic minorities, LGBT, and disabled) results in a paradigm shift for policymakers as it boosts socioeconomic activities. Social inclusion brings prosperity and socioeconomic development and also eradicates poverty [13]. With social and gender discrimination, marginalized groups cannot participate in economic activities [14]. Linking social inclusion with the EE theory helped scholars to investigate how inclusive conditions of a

geographical environment help all communities – without gender, social, and economic discrimination – to explore and exploit new business opportunities.

The effectiveness of entrepreneurial development rests on the assumption of contextual support of nascent entrepreneurial activities. According to the Global Entrepreneurship Monitor (GEM), nascent entrepreneurship explains activities performed before a new business starts. For a successful business venture, both contextual and personal attributes are important for nascent entrepreneurship. For instance, it is optimized through human efforts, creativity, and their ability to scale-up entrepreneurial activities. However, the entrepreneurial environment thrives their efforts towards entrepreneurial nascent activities. Historically, nascent entrepreneurship has remained focused on conventional objective models with recognizing the underlying factors that cause entrepreneurial development [7]. Moreover, limited studies have focused on the predicted outcomes of contextual forces towards nascent entrepreneurship. The recent development of Artificial intelligence (AI) and Machine learning (ML) can provide critical insights on favorable forces that boost nascent entrepreneurial activities. Using AI/ML models can help to identify hidden patterns within inclusive entrepreneurial ecosystem in a more creative way. Understanding of these models is inevitable to drive model precision that helps to predict the outcomes with more accuracy that was not possible earlier.

Therefore, scholars should adopt advanced ML/AI models to reveal new insights with precision and accuracy. Recent development within the field of data science has transformed our understanding about how contextual forces (economic, social and governance) interact towards socioeconomic development [15,16]. It has a deep impact on other domains as well such as business, innovation and management [17]. Following the first machine age, namely the industrial revolution, experts describe ML/AI as a second machine age. However, not much work has been performed to uncover the association between the inclusive EE and entrepreneurial activities using ML/AI.

The modern definition of AI provided by John McCarthy is "the science and engineering of making intelligent machines" [18,19]. ML and AI models have a huge capacity to reason and predict results as compared to human intelligence. Within these models ML is considered as a subpart of AI or deep neural networks. Big data means a large structure, or unstructured or semi-structured data. However, it is critical to note that smaller datasets can also be used to perform ML algorithms (by using neural networks). Entrepreneurial research in the context of ML/AI starts by exploring the aspects that scholars have not witnessed before.

It is emphasized that deep learning algorithms can analyze vast and large data sets of entrepreneurs and identify deep patterns that reflect the success rates of startups [20]. Deep learning and reinforcement learning can be used to model entrepreneurial activities [21]. These models result in predictability with precision and accuracy. More precisely, the field of entrepreneurial development has advanced in methodology and empirical validity of the theoretical perspectives more precisely. Research in the field of entrepreneurship co-evolves with theory and practice. For instance, ML might fill research gaps with knowledge spillover to practice. Previous studies focused on advanced ML techniques to predict entrepreneurship along with mixed methods to achieve robust predictions [21]. Generally, the existing research primarily revolves around the causal links between inclusive factors and entrepreneurship through traditional econometric models. Entrepreneurial development encompasses an important measurable factor, namely inclusive entrepreneurial activities. It is pertinent for scholars to understand the holistic framework of IEE that foster inclusive entrepreneurial activities, including nascent entrepreneurship, especially in developing regions where there is little contributions in the area of inclusive forces fostering entrepreneurial development. For policy makers, it is essential to understand the importance of related factors while deploying resources towards entrepreneurial activities.

The empirical investigation extends our current understanding on how IEE increases the nascent entrepreneurship rate. Scholars have already conceptualized and operationalized the IEE [8]. However, this framework requires one to develop new sights on predictability of IEE. This study uses ML modeling to predict entrepreneurial activities, and to determine feature importance.

The main objective of this study is to perform predictive analysis of nascent entrepreneurial activities using ML models, as well as understand how ML can be used to predict the nascent entrepreneurial activities by using the theoretical framework of the IEE. The IEE theory addresses inclusive growth and inclusive forces work together to foster entrepreneurial activities. The IEE explains the interaction of all actors, and factors are non-linear which requires advanced modeling techniques to capture the dynamic behavior of the underlying forces. Therefore, the theoretical work of the IEE must shift towards integrating machine learning into entrepreneurial research. Nonlinear models capture dynamic interactions, which provide a deeper understanding beyond simple causality. This study's novelty lies in its application of ML models—such as decision trees, random forests, and XGBoost—to predict entrepreneurial activity levels using inclusive factors. While prior studies have predominantly used statistical inferences to explore causality, the current study aims to offer a new methodological approach by focusing on predictive modeling. This study forecasts the entrepreneurial activity across the globe, which helps policymakers and businesses to better understand and anticipate entrepreneurial trends.

2. Problem statement

The literature on entrepreneurial ecosystems has merely focused on individual characteristics, role of institutions, and environmental factors that determine the level of entrepreneurial activities without focusing on their interaction with contextual forces [22]. Since 1980s, the field of entrepreneurship has seen a major shift from personal attributes to broader contextual forces [23]. Within contextual forces, the exclusion of marginalized communities (disabled, ethnic minorities, and LGBTQ) limits the capacity of the economic system to achieve sustainable socioeconomic progression. To address this issue, scholars and policymakers have shifted their focus on inclusive entrepreneurial activities that are important for socioeconomic progression [8]. The social inclusion of policymakers promotes economic activities, which is the key one of the key feature of the SDGs. In this regard, there is a need to empirically test the IEE's role in promoting the entrepreneurial development of all communities without gender, economic, and social discrimination.

Lack of research in explaining the dynamic role of the EE towards fostering socioeconomic development signifies the importance of extending the methodological rigor [24]. Considering the limited scope of linear models, this study has adopted a complex methodological approach aligned with a theoretical framework of the EE to predict nascent entrepreneurial activities. Scholars have always been curious about how methods support theories more dynamically. ML models can better predict and measure the rate at which entrepreneurial activities across all group increases. By improving the predictions of entrepreneurial activities, policy interventions can promote the IEE that could foster economic growth and social well-being.

A critical challenge for policymakers is to measure social progression, which is considered an important outcome of an IEE that propagates inclusive education access, equality, and institutional quality. The value creation process is determined by the social dimension that supports promoting sustainability [25,26]. Policymakers concern related to socioeconomic development can be addressed through an IEE that promotes social inclusion that leads to economic and sustainable development.

Policymakers and scholars have yet to understand how the IEE concept linked with SDGs encourages equal participation of all communities in socio-economic development process [27].

The study mainly focuses on outcomes that reveal the level of nascent entrepreneurial activities that are influenced by inclusive factors integral to fostering entrepreneurial development. Understanding and accurately predicting the entrepreneurial activity is crucial to drive initiatives that support entrepreneurship and economic progress. Machine learning models are vital for this research because they can process vast amounts of data, identify complex interactions, and provide highly accurate predictions.

Unlike traditional statistical methods, ML can uncover patterns in the data that might not be apparent in a linear model, thus offering more robust predictions for entrepreneurial activity. These models can adapt to new data, which is crucial for continuously evolving economic landscapes. Applying ML techniques such as random forests and XGBoost will enable this study to optimize the prediction models for nascent entrepreneurs or new business owners who have been running their business and have been paying salaries for more than three months as per definition of Global Entrepreneurial Monitor (GEM) but not exceed 42 months, thereby helping policymakers and researchers develop more targeted strategies to promote entrepreneurship.

This study bridges the theoretical and research gaps by employing ML techniques to predict entrepreneurial development based on inclusive factors, thus contributing novel insights into entrepreneurial development. ML's predictive capacity offers an invaluable tool for advancing entrepreneurship research and foster economic growth. The theoretical contribution extends the IEE theory from a descriptive analysis to predictive optimization. This predictive analysis shifts the current understanding of ecosystem elements and uncovers how they predict nascent entrepreneurial activities.

3. Research gap

Scholars and policymakers emphasize the importance of understanding entrepreneurship using nonlinear model [28]. In ML complex tasks can be handled through supervised ML [29]. However, while ML/AI are used to analyze big data, they are limited in the surveillance of contemporary inclusive nascent entrepreneurial activities [29,30].

Within the context of the IEE, previous studies have been limited in explaining how to use ML/AI for forward thinking. Limited studies have focused on employing ML to predict entrepreneurial nascent activities. Entrepreneurship is considered as the primary driving force of socioeconomic development [31,32]. The initial stage of entrepreneurial development process is considered as the nascent entrepreneurship. However, nascent entrepreneurial activities should be inclusive that is yet to be explored by researchers within the context of inclusive entrepreneurial activities. Recently, the factors of inclusive entrepreneurial ecosystems have been conceptualized and operationalized [8]; however, empirical evidence on how inclusive entrepreneurial ecosystem influence nascent entrepreneurship is still underdeveloped.

According to the SDGs, socioeconomic development can be achieved by focusing on SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure) [33]. Furthermore, one important SDG that addresses the inclusive participation of all stakeholders brings prosperity in a region. Traditional entrepreneurship literature has not focused on marginalized communities such as ethnic minorities and disabled communities. This restricts marginalized groups in having equal participation within economic activities. Therefore, including diverse groups in socio-economic activities promote innovation and adaptability [34]. Further, an Inclusive entrepreneurial ecosystem provides a supportive environment in terms of resources, policies, and market accessibility

for all communities and promote entrepreneurial activities [8]. The extension of IEE is on theoretical underpinning of entrepreneurial ecosystem that explains the interconnected elements propagate entrepreneurial development in a region [35]. Scholars have highlighted the importance of adopting computational methods for a deeper understanding of entrepreneurship [6]. Secondly, governments and development organizations can leverage machine learning insights to design targeted interventions that promote inclusive entrepreneurship, particularly in underserved regions, which is beneficial for policymakers [36]. Using supervised machine learning, ML provides predictive accuracy for Investors, accelerators, and business incubators who can identify high-potential entrepreneurial ventures and support them more effectively [37]. As ML/AI models capture the non-linear relationship and helpful to make predictions with more accuracy.

This study raises the question of what is the non-linear relationship between an IEE and nascent entrepreneurship. This answer directly contributes to the IEE theory. EE context contains multiple factors that interact in a dynamic and complex way. Therefore, conventional models add to the theoretical progression of this field. In this regard, this study addresses significant contributions in the field of EE by embracing empirical findings. The outcome of the study brings key factors along with their relative performances to contribute towards socio-economic development. Scholars and policymakers can simulate their policy decisions by using parametric values of the selected model. Finally, this study explores how the IEE predict nascent entrepreneurial activities.

3.1. Theoretical perspective

The study is explicitly grounded in entrepreneurial ecosystem theoretical perspective [3,7]. This theory is extended by [8], where authors conceptualized and operationalized related dimensions of inclusive entrepreneurial ecosystem. It uses multidimensional constructs including resources, governance, culture and markets. Construct validity is established through Kaiser Meyer Olkin (KMO >0.7) and Bartlett's test ($P < 0.001$) using 115 country panel data. It is theory driven conceptualization of the proposed framework rather an ad hoc variable selection. The valid framework is used to apply predicted modeling. Moreover, the dynamic capability theory broadly operates at a firm level; however, this study actually operates at a country level ecosystem. This study addresses which ecosystem configurations predicts nascent entrepreneurial activities.

The integration of the IEE theory with optimization is based on ML models that forecast nascent entrepreneurship, which is considered as a critical gap in the current field of entrepreneurship. The contributions are threefold in the theoretical, methodological, and practical domains: the theoretical contribution extends the IEE research into predictive modeling; the methodological contribution demonstrates ML/AI modeling for nascent entrepreneurship prediction; and finally, the practical contribution provides feature importance for policymaking implications, which align with the SDGs.

4. Literature review

The entrepreneurial development process explains how social groups identify new business opportunities and exploit them effectively [31]. Entrepreneurial development focuses beyond interaction of individual attributes and environmental forces; instead, it extends the role of all actors and factors who interact to prompt productive entrepreneurship towards socio-economic development. The theoretical evolution of the EE explain the interaction of actors, institutional, and governance elements [38]. This theory extends from personal attributes to contextual, spatial, and temporal dimensions, and furthermore also acknowledges that the role of human capital, culture, finance, and

infrastructure are interdependent and interconnected in a region to produce new business opportunities [39–41]. However, the role of all dimensions needs a holistic understanding in the way they interact and achieve the desired outcomes. The EE explains the interaction between individual factors and environmental forces. Recent developments of the EE field has shifted towards an inclusivity perspective. Moreover, the notion of the EE in the context of inclusivity requires theoretical justification to integrate with solving complex relationships of related factors [6]. Historically studies have been mainly focused on addressing the main outcomes, such as entrepreneurial activities and nascent entrepreneurship, in association with the antecedents, including economic, cultural, and social structures [42]. However, the association of these structural factors with the behavioral traits and accessibility of resources has remained a challenge among researchers and scholars. Individual level variables alongside structural and other systemic factors such as inclusivity, diversity, and resilience interact in a complex way. Their complex interaction is labeled as an EE [8].

The ecosystem concept is borrowed from biology, thereby reflecting on how species interact in a natural habitat and evolve. They share certain characteristics, such as complexity and nonlinearity, indicating there are dynamic, adaptive, and emergent systems that rely on multiple interactions and feedback loops among their constituents [43]. However, their purposes and dimensions are distinct. Later, the ecosystem concept is used in business ecosystem that focuses on how firms can leverage their relationships with other actors of ecosystem to create competitive advantage. Further innovation ecosystem concept is conceptualized that is concerned with process of innovation including process and system level transformation. The paradigm shift in the field of entrepreneurship occurred when the idea of entrepreneurial ecosystem started emerging in between 1980s and 1990s. In this era, entrepreneurial studies had shifted from individualistic perspective towards broader societal context including culture, economic and social forces [44]. It was argued that one group of actors cannot control resources by themselves unless markets, government support, and institutions channelize their efforts. The entrepreneurs from both public and private sector come together and build industrial infrastructure to promote entrepreneurial activities. Entrepreneurial ecosystem focuses level of support provided by environmental contextual factors along with personal attributed to produce entrepreneurial development. Table 1 shows the exclusive difference among various types of ecosystems.

Table 1. Evolution of ecosystem concept.

Ecosystems	Business ecosystems	Innovation ecosystems	Inclusive ecosystems	Entrepreneurial ecosystems
Definition	The economic interactions create through the relationship between various stakeholders including customers, and suppliers.	Focus on knowledge sharing and collaboration among stakeholders that cultivate creativity.	The inclusive context promotes equitable opportunities for wide range of diverse groups, and removing social and economic discrimination.	EE promotes holistic perspective interconnected and interdependent stakeholders including industry, investors, and organizations.

Recent developments in the literature focused on regional and social factors that influence entrepreneurial infrastructure. Now, the entrepreneurial context broadened in its scope and now includes spatial and temporal markets alongside social dimensions [45]. Within this broad context, the literature has not focused on inclusive factors that are important for entrepreneurial development but are crucial to foster entrepreneurial activity [8,46]. Empirical studies have shown financial capital, educational opportunities, and networks play a pivotal role in enabling entrepreneurship [3]. For

instance, by analyzing the data from various countries, it is found that inclusive markets, characterized by equitable access and reduced entry barriers, significantly enhance the entrepreneurial outcomes [4]. Empirical studies have witnessed the role of governance and its support toward entrepreneurial development [38]. It is witnessed that countries with more inclusive governance structures exhibit higher levels of entrepreneurial development [39]. Furthermore, the inclusive cultural factors, such as societal norms embrace risk-taking and innovation that are strongly associated with entrepreneurial nascent activities across different regions and societies [47]. However, these studies have demonstrated mixed results and showed limited explanations regarding their collective interdependent role towards entrepreneurial activities. In fact explain the interdependency of all factors and show that their complex interactions enhance entrepreneurial activities.

Inclusiveness promotes equity in resource sharing among all stakeholders. It allows all communities to openly participate and have equal access of resources. These contextual conditions promote socioeconomic development as everyone has an equal opportunity to explore and exploit the available resources. Therefore, inclusiveness requires a holistic or systemic approach within EE entrepreneurial ecosystem and it encompasses the policy framework, structure and supportive environment of entrepreneurial activities for all communities [48]. Previous studies have given less attention on inclusiveness context within the EE, which is an important outcome according to the SDGs [49]. Inclusiveness refers to the equal participation of all stakeholders in entrepreneurial activities [50].

The inclusiveness of socioeconomic progression follows principles of equal opportunities and equity in the distribution of resources. It is essential to achieve inclusive growth; policymakers use policy instruments along with the active involvement of all stakeholders, including non-government organizations (NGOs), businesses, government, and social target groups (e.g., transgender).

Inclusive resources foster entrepreneurial activities that include training, finances, education, technology, and skills/competencies. Inclusive culture welcomes inclusive societies and accepts marginalized communities. It includes freedom of expression, and gender acceptability. Inclusive governance, and inclusive markets support all communities through rules and regulations and the accessibility of markets [8].

Previously, many studies have found the significant role of inclusive factors on entrepreneurial activities. In a cross-country analysis they found that inclusive factors provide an important contribution towards entrepreneurial activities [51]. However, the model that was used only captured linear relationship and had limited power to make predictive relationships. Additionally, other inclusive factors, including markets and governance, have influenced entrepreneurial development [52]. While the study provided valuable insights into the causal mechanisms, it lacked a predictive component, thus leaving a gap in understanding how these factors interact to influence future entrepreneurial trends [52]. The inclusive cultural factors have a significant impact on entrepreneurial activities [53]. However, the methodological approach limited their ability to predict the entrepreneurial activity under different contexts and boundary conditions of a region [53]. The economic context has a supportive role for entrepreneurial activities. Studies have identified the association of inclusive institutions and infrastructure, with entrepreneurial activities having a critical role in fostering entrepreneurial development [54,55]. However, traditional economic models have limitations in accurately predicting the future of entrepreneurial nascent activities. This gap could be addressed using ML models.

While the empirical studies have discussed the understanding of how inclusive factors impact entrepreneurial activity, there are significant gaps in their approaches. First, most studies rely on regression models, which focus on inferring causality but are limited in their ability to capture non-linear and complex relationships between variables. These models often assume that relationships are

stable over time, which may not accurately reflect real-world dynamics. Second, empirical studies have often been constrained by small datasets or a limited geographic scope. For instance, previous studies have focused on European countries, thus leaving open question of whether their findings are generalizable to other regions [51,52]. Additionally, their reliance on static models limits the ability to forecast future entrepreneurial trends, which is crucial for policymaking and strategic planning. Third, very few studies have explored the use of ML in entrepreneurship research. ML models, such as decision trees, random forests, and XGBoost, offer the potential to address these gaps by capturing complex relationships and improving the accuracy of predictions. Additionally, these models can also analyze large and diverse datasets, providing insights into how inclusive factors dynamically influence total entrepreneurial development. Most studies on nascent entrepreneurship do not incorporate the theoretical framework of inclusivity, which is crucial to understand how diverse socio-economic groups participate in entrepreneurship [56].

The reliance on traditional statistical methods limits the predictive capacity of studies, as these methods assume linear relationships and ignore the complex interactions between the EE components [57]. Policymakers could not drive actionable results out of the static models. They need dynamic predictions to make timely and accurate decisions [3]. Therefore, methods should perfectly align with research hypothesis in order to validate the underlying theories. Recent studies have conceptualized IEE that requires further investigations of their complex association with the real world [8]. This framework emphasizes four key inclusive factors: Inclusive Resources, Inclusive Governance, Inclusive Markets, and Inclusive Culture. The importance of an IEE can be witnessed from real-world examples, such as the Silicon Valley EE demonstrate how an inclusive access to resources, including venture capital, mentorship, and technological infrastructure, fosters high levels of innovation and business success [58]. On the other hand, there are many economies around the world struggling to access inclusive governance and market inclusive accessibility such as Nigeria and Bangladesh, thus leading to lower participation of nascent entrepreneurship [37].

Additionally, past studies have witnessed the role of the ecosystem towards boosting entrepreneurial activities. For instance, Startup India and Brazil's SEBRAE showcases the importance of inclusive governance to propagate public policies and actively create opportunities for marginalized entrepreneurs [36]. This transition reflects the importance of studying the systemic perspective of entrepreneurship leveling up from a human centric approach. The integration of ML techniques, as demonstrated in the study that utilized XGBoost, Random Forest, and Decision Tree models, represents a methodological breakthrough in predicting entrepreneurial nascent activities across a region. The conceptualization of inclusive resources has witnessed the most influential predictor of early-stage entrepreneurial activity, thus reinforcing the argument that equal access to financial, technological, and human capital is critical for entrepreneurial success. Second, inclusive Governance and Inclusive Markets play substantial roles, indicating that institutional quality, regulatory support, and market accessibility significantly shape entrepreneurial opportunities [59]. Finally, Inclusive Culture exhibits a varying but notable impact, suggesting that social norms and cultural perceptions of entrepreneurship influence entrepreneurial motivation and sustainability [8,57]. In addition, previous studies mostly focused on conventional statistical models as they hold value in predicting the model results that closely match with reality. However, reality is dynamic and complex, which requires complex models that capture the model's accuracy by capturing its non-linear relationship. Therefore, recent advancements in the field of AI have enabled researchers to adopt advance models by providing model weights that are more generalized towards theoretical frameworks. By employing ML, the study provides a dynamic, predictive, and data driven approach to entrepreneurial research, thus equipping policymakers with more precise tools to foster inclusive economic growth [8]. This critical literature

review underscores the need to move beyond traditional approaches to study entrepreneurial activity by integrating IEE theory and ML methodologies. Inclusive entrepreneurship provides foundational framework to understand the inclusion of all stakeholders [8]. ML based predictive models offer a novel methodological tool. As global economies strive for sustainable and inclusive growth, embracing these innovative research paradigms is not just an academic necessity but a policy imperative.

This study aims to bridge the gaps identified in the literature by applying ML techniques to predict nascent entrepreneurship levels based on inclusive resources, governance, culture, and markets. Unlike previous studies that focused on causality, this research will utilize ML models—such as logistic regression, decision trees, random forests, and XGBoost—to predict entrepreneurial activity. These models can uncover hidden patterns in the data that traditional methods may overlook, thus offering a more nuanced understanding of how inclusive factors interact to drive entrepreneurship nascent. Moreover, this study will take a global approach by analyzing data from various regions, thus addressing the limitations of previous studies that were geographically constrained. By improving the accuracy of predictions, this study will contribute to the broader literature on entrepreneurship and sustainable development, offering valuable insights for policymakers, businesses, and researchers. Finally, by aligning with the SDGs, particularly SDG 8 and SDG 9, this study will demonstrate how fostering inclusive entrepreneurship can contribute to sustainable economic growth. However, the SDGs 4 and 10 are also embedded in the IEE, which emphasize equity and reduce the regional disparities. By using advanced predictive models, this research will provide actionable insights that can help governments and organizations develop strategies to support entrepreneurship and achieve the SDGs. While previous empirical studies have deepened our understanding of the role of inclusive factors in driving entrepreneurial activity, they have been limited by their methodological approaches and geographic focus. This study will fill these gaps by applying ML models to predict nascent entrepreneurship levels globally, thus offering new insights into the dynamic relationships between inclusive factors and entrepreneurship. By doing so, this research will contribute to the achievement of the SDGs and provide practical guidance to foster inclusive and sustainable entrepreneurial development.

In the context of inclusive entrepreneurship, it invites all stakeholders to leverage entrepreneurial activities at a high rate within the EE. In this case, distinct ecosystems are required to facilitate and support in significantly different ways than a traditional EE [12,57]. The inclusive entrepreneurship concept is defined as the representation and participation of marginalized groups in the entrepreneurship development process. It facilitates them by addressing their social and economic problems [59]. It encompasses the entrepreneurial activity that embraces inclusive opportunities [60], inclusive participation, and sharing inclusiveness [61]. By considering the realized and intended impact of inclusive entrepreneurship, it differs significantly from conventional entrepreneurship.

The current field of entrepreneurship is evolving towards the utilization of AI models [62,63]. Scholars have highlighted the role of AI to explore entrepreneurial practices in the area of automation, data driven decisions, and ML applications that guide in predicting new opportunities [20]. However, few studies have recently started exploring the integration of advanced AI models in the field of entrepreneurship. A recent study that used the Delphi technique identified AI as important theme that to shape entrepreneurship's future by 2030. Moreover, scholars have critical concerns about AI applications in entrepreneurial research, and state that it is still fragmented [64].

Previous empirical studies have validated and established the legitimacy of using of ML in the field of entrepreneurship. For instance, previous studies have used ML models for investment decision making [65]. Additionally, scholars have also acknowledged the prediction of startup success is a critical aspect of entrepreneurship research [66]. ML models, including Random forest, and gradient

boosting, are considered robust algorithms that provide robust analyses for startups outcomes by achieving up to 82 % accuracy [67]. More importantly, entrepreneurship theories are built around how to manage uncertainty. By using AI algorithms researchers can reduce the uncertainty by identifying hidden patters within the large datasets [64]. However, entrepreneurship research predominantly focuses on startup success, venture capital investments, and risk assessments, which are firm based the outcome indicators. Considering this limitation, the integration of ML applications at the ecosystem level has not yet been considered [68].

This study extend the current body of knowledge by optimizing ML applications and integrating ML algorithms at the country level, which includes the IEE dimension and feature importance rather just driving prediction on the basis of ML models. Moreover, this study attempts to connect policy makers and their strategic decisions to prioritize the IEE factors to achieve sustainability in a region.

Considering the current debate on methodological challenges of integration of ML in entrepreneurship research, scholars have started to recognize the importance of this paradigm [69]. ML usage is not limited to just optimizing the predictive accuracy; it advances in SHapley Additive exPlanations values and permutation importance. For policymakers, it provides a feature contribution analysis. This study goes beyond econometric approaches, thereby merely focusing on the internal validity and unbiased treatment effect.

5. Methodology

This study seeks to understand the contextual inclusive conditions of the EE that influences the nascent entrepreneurship. The data is taken from a recent study on an IEE, where a global index is developed on this construct [8]. The present study uses the most recent GEM data set, and "nascent entrepreneurship" is taken as the outcome variable. The core objective of this study is to examine the influence of an IEE on nascent entrepreneurship. Four related dimensions are taken to predict nascent entrepreneurship: inclusive culture, inclusive markets, inclusive resources, and inclusive policies. In this regard, ML models are used to identify predictive patterns and assess relative importance of these variables. This objective aligns with the conceptual framework established in prior work [8]. Table 2 shows the related variables and relevant indicators of each dimension, along with the definition and sources given. Each variable follows conceptualization and operationalization and is linked to the underlying theoretical justification.

Table 2. Inclusive entrepreneurial ecosystem variables.

Variables	Indicators	Definition (Units)	Source
Inclusive Resources	Advanced Education	Tertiary education (years)	SPI
		Advanced education of females (%)	
		Quality weighted universities (points)	
		Number of citations documents (documents/1,000)	
		Academic freedom (0=low; 1=high)	
	Basic Knowledge	No schooling of females (% of women)	SPI
		Primary school enrollment (% of children)	
		Secondary school attainment (% of population)	
	Essential services	Access to essential services	SPI

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	Information and Communications	Subscriptions of Mobile phones (subscriptions/100 people) Media censorship (0=frequent; 4=rare) Internet users (% of pop)	SPI
	Justice awareness	Justice accessibility (0=non-existent; 1=observed)	SPI
	Online governance	Governance online (0=low; 1=high)	SPI
	Quality education	Quality education and equal accessibility (0=unequal; 4=equal)	SPI
	Financial activities and services	Financial services affordability (0=low; 1=high)	SPI
Inclusive Policies	Political power by gender	Equality of political power by gender (0=unequal power; 4=equal power	SPI
	Political power by social group	Equality of political power by socioeconomic position (0=unequal power; 4=equal power)	SPI
	Political power by socio-economic position	Equality of political power by social group (0=unequal power; 4=equal power)	SPI
	Government Support policies	The extent to which public policies support entrepreneurship - entrepreneurship as a relevant economic issue	GEM
	Governmental programs	Inclusive government policies	SPI
	Decisions of government officials	Favoritism in decisions of government officials, 1-7 (best)	SPI/WEF
	Government regulation	Burden of government regulations	SPI
Inclusive culture	Acceptance of all Genders	Acceptance of marginalized gender (0=low; 100=high)	SPI
	Discrimination and violence against minorities	Discrimination and violence against minorities (0=low; 10=high)	SPI
	Freedom of expression	Freedom of expression (0=no freedom; 1=full freedom)	SPI
	Freedom of religion	Freedom of religion (0=no freedom; 4=full freedom)	SPI
	Gender parity in secondary attainment	Gender parity in secondary attainment (distance from parity)	SPI
Inclusive Markets	Internal market openness	Freedom to enter existing markets	GEM
	Internal market dynamics and stability	Change in market dynamics from year to year	GEM
	Market Efficiency	The Goods Market Efficiency Index	WEF
	Domestic market size	Gross domestic product (GDP) based on the purchasing-power-parity (PPP) (billions).	WEF

*Note: Source: (Hameed et al. [8])

115 countries were taken to model the dataset. The dataset is taken from the Social Progress Index, the World Economic Forum, and the GEM index. After removing the missing values, there are 4964 data points of inclusive resources and governance, 9528 data points of inclusive culture, inclusive market includes 6990 and 8515 data points of nascent entrepreneurship. In order to test the model, we utilized a standard practice of 70-30. Therefore, the chosen sample for training and testing provided a meaningful evaluation. ML is for the most predictive modeling, and not meant to be used to infer causal relationships between input variables and some studied output. In previous studies, scholars have used ML tools to predict business outcomes such as eco-finance networks and to simulate corporate economic behaviors [70].

There are two issues when applying ML models in social sciences: the first deals with technical lacking and the second research traditions focus on limited datasets to perform advanced models. With the advancement of data footprints of social science captured by famous world indexes, social science fields are invited to apply advanced models such as logistic regression, decision tree, random forest, and xgboost.

Before applying ML models, missing values and outliers are handled. There are multiple strategies to handle missing values such as imputation using mean/median. Considering the large dataset, the missing values can be handled the imputation method by taking the mean value.

The following Figure 1 shows that inclusive resources and inclusive culture contains fewer outliers. However, inclusive governance and inclusive markets appear to have balanced distributions with fewer extreme deviations. It can be seen that the models use large dataset and these outliers may not severely impact the model's performance.

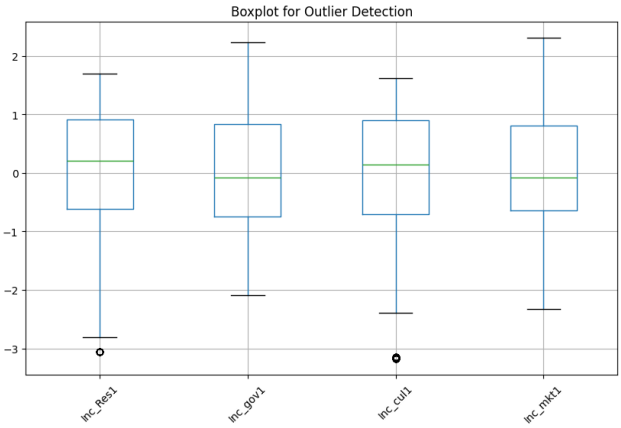

Figure 1. Outlier detection.

Panel data models are often used in economic studies where the data is comprised of multiple entities (such as countries or firms) observed over time. These models are advantageous for controlling unobserved heterogeneity across entities and over time, using techniques such as fixed and random effects [48]. However, despite their widespread use in entrepreneurship studies, panel data models may not be the most appropriate approach for all research questions, particularly when non-linear relationships and complex interactions exist among variables. Traditional panel data models, such as fixed and random effects models, heavily rely on linear relationships between the independent and dependent variables [71]. In this study, the relationships between variables such as Inclusive Resources, Inclusive Government, Inclusive Culture, and Inclusive Markets and the outcome variable nascent entrepreneurship are likely non-linear.

This complexity limits the explanatory power of panel data models, which are not well-suited to capturing non-linear interactions between variables [72]. In an IEE, variables like government policy and market inclusiveness likely non-linearly affect entrepreneurial activities. For example, access to resources may have diminishing returns as the ecosystem becomes saturated. Panel data models typically assume constant marginal effects, which is a limitation in capturing the true nature of such diminishing returns or threshold effects [73]. XGBoost and Random Forests are ML models that capture non-linear relationships between the inputs and the output features [74]. Unlike linear models, using these models closely handles more complex relationships related to reality. The selected models capture nonlinear interactions and feature importance which determine usefulness for robust analysis on small samples. This rationale is aligned with the study's objective that focuses on optimization and prediction of nascent entrepreneurial activities with accuracy. It is important to note the current limitation of ML models that they do not capture permanent structural relationship but capture conditional patterns

In this study, an IEE is a complex phenomenon with inclusive resources, markets, and cultural dimensions. Their predictability towards entrepreneurial activities remained challenging for researchers [75]. However, this could be captured through XGBoost, Random Forests, and a decision tree model. ML models are more capable of handling high-dimensional data and identifying interactions between variables that traditional econometric models, including panel data models, struggle to capture [76]. The equations of each model are given below.

$$X_1 = \text{Inclusive resources},$$

$$X_2 = \text{Inclusive policies},$$

$$X_3 = \text{Inclusive culture},$$

$$X_4 = \text{Inclusive markets},$$

5.1. XGBoost

XGBoost predictions combine multiple trees to minimize error:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i),$$

$\hat{y}_i$ which predicts the nascent entrepreneurship for data point, i
K = Number of decision trees,
$f_k(x_i)$: Prediction from tree k based on the input vector x_i of the variables [inclusive resources, inclusive policies, inclusive culture, inclusive markets.

The objective function (loss + regularization) is minimized as follows:

$$\text{obj}(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k),$$

y_i : True nascent entrepreneurship,
l : Loss function (e.g., squared error),
Ω : Complexity regularization on trees,

This model follows gradients and Hessians optimize the model by improving the ensemble of trees to better predict the outcome.

5.2. Decision tree

A decision tree partitions the data by choosing the best splits on variables to minimize impurities or variance. For the regression, the prediction at leaf m is as follows:

$$\hat{y}_m = \frac{1}{N_m}\sum_{i\in R_m} y_i,$$

$$R_m : \text{Region of data points in leaf } m,$$

$$N_m : \text{Number of points in leaf } m,$$

y_i : Observed outcome (nascent entrepreneurship).

The tree recursively splits attributes or features (for instance inclusive resources, policies, etc.) by either maximizing the information gain or by minimizing squared error loss until the stopping criteria are fully addressed.

5.3. Random forest

A Random Forest functions on the basis of decision trees using bootstrap samples and random feature subsets. The prediction for a new data point x is the average of predictions from all M trees:

$$\hat{y} = \frac{1}{M}\sum_{j=1}^{M} h_j(x),$$

$$hj(x) = \text{Prediction of the } j^{th} \text{ decision tree for input } x,$$

$$M = \text{Total number of trees}$$

Each tree uses random subsets of variables (e.g., inclusive resources, policies, culture, and markets) to create diverse models, thereby reducing variance and improving the generalization.

5.4. Suggested mathematical equations according to the proposed model

5.4.1. *XGBoost model*

$$\hat{y}_i = \sum_{k=1}^{K} f_k(\text{resources}_i, \text{policies}_i, \text{culture}_i, \text{markets}_i).$$

Minimize the following:

$$\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \sum_{k=1}^{K} \Omega(f_k).$$

5.4.2. *Decision tree prediction*

$$\hat{y}_m = \frac{1}{N_m}\sum_{i\in R_m} y_i,.$$

with splits based on conditions of inclusive variables such as inclusive culture, policies, resources, and marekts.

5.4.3. *Random forest prediction*

$$\hat{y}_i = \frac{1}{M}\sum_{j=1}^{M} h_j(\text{resources}_i, \text{policies}_i, \text{culture}_i, \text{markets}_i).$$

These models help to transform the complex association of inclusive factors and entrepreneurship. These mathematical equations act as functions that optimize the prediction accuracy, which is an essential objective of this study. Furthermore, these equations, measure and quantify the variable significance and complex interactions. This follows rigorous process of tree structures, gradient boosting, and ensemble averaging.

While these models provide robust findings, there is a tradeoff of loss minimization, variance reduction, and model regularization embedded within these algorithms. Therefore, this study achieves robust findings on how inclusive resources, policies, culture, and markets drive nascent entrepreneurship.

These equations provide the basis to capture the way each model learns relationships between inclusive variables and nascent entrepreneurship. Regularization and tree depth control help balance bias and variance.

For instance, the combined effect of Inclusive Culture and Inclusive Government on entrepreneurial outcomes can be effectively modeled by tree-based algorithms such as Random Forests, which excels in modelling complex interactions without pre-specification by the researcher. Overfitting issues can be handled in ML methods like XGBoost and Random Forest, especially when cross-validation and regularization are required in the application [77]. Unlike a panel data analysis, where overfitting undermines the model's accuracy, ML models ensure that the model generalizes well to unseen data in the study.

XGBoost, Random Forests, and Decision tree models are used in this study, and they are famous for their robustness in handling non-linear relationships. These models are used in the predictive modeling of entrepreneurial outcomes. Using random search with cross validation, such as a 5-fold approach, is used to optimize parameters such as the learning rate, the number of trees, and the maximum depth of decision trees. Further model evaluation is based on specific metrics such as the model accuracy, precision, recall, and F1-score. Finally, the area under the ROC curve (AUC) is analyzed with the justification that these metrics provide a comprehensive assessment of the predictive performance of nascent entrepreneurship.

ML models identified Inclusive Resources as the most important driver of entrepreneurial activity across all models. This finding suggests that the access to resources such as capital, infrastructure, and knowledge is paramount to fostering entrepreneurship, more so than government policies or cultural factors, which were previously considered to be equally important [78]. The ML models demonstrated that the effects of an Inclusive Market on the entrepreneurial activity are non-linear, which indicate that while favorable market conditions are crucial, their impact may plateau or even diminish under certain conditions. This insight adds depth to our understanding of EE, which is difficult to capture with traditional linear panel data methods [22]. The ability of machine learning models to handle complex interactions provides a deeper understanding of the interconnectedness of the ecosystem components. For example, the combined impact of Inclusive Government and Inclusive Culture on entrepreneurship can now be understood as synergistic rather than additive, offering new pathways for policy intervention.

While panel data models are valuable to control unobserved heterogeneity and explore linear relationships, their limitations in capturing non-linear and complex interactions make them less robust

for this study. The ML models employed here—XGBoost, Decision Trees, and Random Forests—provide a more flexible and powerful framework to analyze the intricate relationships within an IEE. These models not only reveal the key drivers of entrepreneurial activity but also uncover novel insights into the non-linear and interconnected nature of the ecosystem components, thus offering richer, data-driven perspectives for fostering entrepreneurship. In this context, one of the key advantages of ML models is the ability to automatically assess the importance of features. In this study, ML models identified inclusive resources as the most important factor to promote early-stage entrepreneurial activity. This is a novel finding, as traditional econometric models typically require manual interaction terms or transformations to test such relationships.

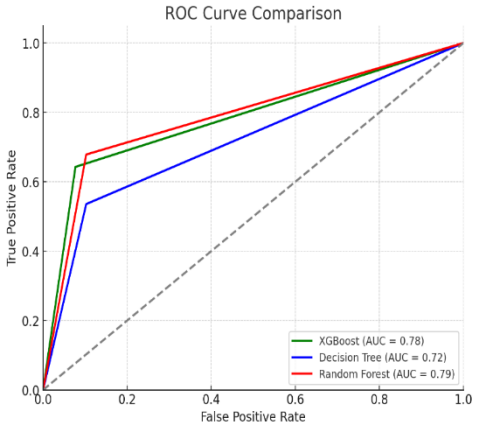

Figure 2. ROC curve.

6. Model performance interpretation

The model hyperparameters are optimized using accuracy, recall, and AUC, which are considered primary evaluation criteria. For the classification performance, a ROC analysis is employed, but SHAP values provide feature contributions across the ML models [79]. Accuracy is calculated as the ratio of correct predictions to the total predictions. The results of the study demonstrates that XGBoost and Random Forest have the highest accuracy at 0.80597 (Table 3 and Figure 2). It means that these models correctly predict nascent entrepreneurship 80.6% of the cases. Furthermore, the Decision Tree has a lower accuracy at 0.746269 (74.6%). Sensitivity, also known as recall, measures the proportion of actual positives that are correctly identified by the model (true positives). Additionally, a sensitivity analysis of these models represents the model's adequacy in predicting the outcome. Random Forest performs the best with a sensitivity of 0.678571 (67.9%), closely followed by XGBoost at 0.642857 (64.3%). Finally, the Decision Tree has lowest sensitivity level, about 0.535714 (53.6%). Therefore, the analysis reveals that random forest is better than the other models.

Table 3. Model performance.

Model	Accuracy	Sensitivity (Recall)	Specificity	AUC
XGBoost	0.80597	0.642857	0.923077	0.782967
Decision Tree	0.746269	0.535714	0.897436	0.716575
Random Forest	0.80597	0.678571	0.897436	0.788004

Specificity measures the proportion of actual negatives that are correctly identified by the model (true negatives). XGBoost shows the highest specificity at 0.923077 (92.3%), meaning it is the most effective at correctly identifying negative cases. Decision Tree and Random Forest have a slightly lower specificity at 0.897436 (89.7%). The AUC measures the model's ability to distinguish between classes, where higher values indicate better performances. Random Forest has the highest AUC at 0.788004, thus suggesting that it has the best overall ability to differentiate between positive and negative cases. XGBoost is close behind with an AUC of 0.782967, and Decision Tree has the lowest AUC at 0.716575.

6.1. Feature importance interpretation

Table 4. Feature importance.

Feature	XGBoost Importance	Decision tree importance	Random forest importance
Inclusive Resources	0.480633	0.479713	0.375506
Inclusive Government	0.177016	0.171196	0.189652
Inclusive Culture	0.161584	0.109753	0.24455
Inclusive Market	0.180767	0.239337	0.190293

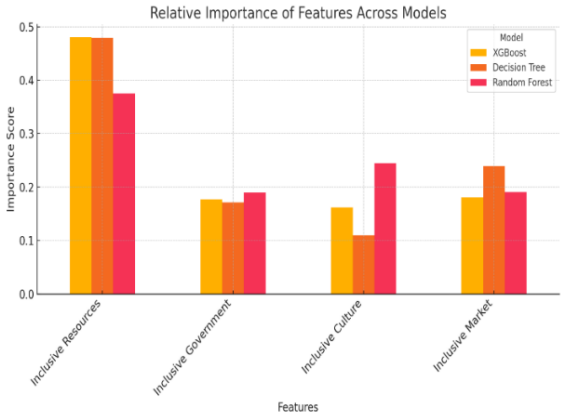

Figure 3. Feature importance.

Figure 3, highlights the feature importance of predictors across all three models. Table 4, shows that XGBoost has highest importance at 0.480633, followed by the Decision Tree at 0.479713 and Random Forest at 0.375506. This suggests that the access to resources is the most critical factor to predict the outcome. Inclusive Government is the second most important feature for Decision Tree (0.171196) and XGBoost (0.177016), while Random Forest gives it a slightly higher importance (0.189652). This indicates that governance is a consistently significant factor, although less so than resources. Inclusive Culture has moderate importance across the models. It is ranked third in XGBoost (0.161584) and Decision Tree (0.109753), while Random Forest gives it a higher weight (0.24455), suggesting that Random Forest may consider cultural factors more significant than the other models. Inclusive Market ranks as a moderately important factor in all models, with XGBoost assigning it a weight of 0.180767, Decision Tree giving it 0.239337, and Random Forest assigning it 0.190293. This shows that the access to inclusive markets is also a key predictor, though not as influential as resources or governance.

The findings are aligned with one of research objective to transform complex associations through mathematical equations and to predict the accuracy. The results use algorithms that reveals hidden pattern of how inclusive forces drive entrepreneurial activities.

Table 5 summarizes the key hyperparameter settings for the three ML models. Decision Tree has a maximum depth of 6. Furthermore, a minimum of 5 samples are required to split a node, which balances the flexibility and helps control. Second, Random Forest is employed on a large ensemble of 500 trees. Furthermore, it has shallow individual trees with a maximum depth of 3 and a minimum sample split of 5. These five features are considered at each split that promotes robustness and variance reduction while maintaining reproducibility. Gradient Boosting (XGBoost) was specified with 100 boosting iterations. Additionally, it shows a learning rate of 0.3 with a maximum tree depth of 6. Moreover, L2 regularization shows a strength of 3 and full data subsampling. Finally, it enables the capturing of complex nonlinear relationships and controlling overfitting by regularization and replicable training.

Table 5: Model hyperparameter summary.

	Model	Parameter value
0	Decision Tree	Maximum Depth 6
1	Decision Tree	Minimum Samples Split 5
2	Decision Tree	Replicable Training Yes
3	Random Forest	Number of Trees 500
4	Random Forest	Maximum Depth 3
5	Random Forest	Minimum Samples Split 5
6	Random Forest	Maximum Features 5
7	Random Forest	Replicable Training Yes
8	Gradient Boosting (XGBoost)	Number of Estimators 100
9	Gradient Boosting (XGBoost)	Learning Rate 0.3
10	Gradient Boosting (XGBoost)	Maximum Depth 6
11	Gradient Boosting (XGBoost)	Regularization Strength (Lambda) 3
12	Gradient Boosting (XGBoost)	Subsample 1.0
13	Gradient Boosting (XGBoost)	Replicable Training Yes

7. Geographical footprints of nascent entrepreneurship

Across all models, inclusive resources consistently emerged as the most important feature to predict early-stage entrepreneurial activity. This suggests that the access to resources is a critical factor in fostering entrepreneurship. Additionally, Inclusive Market had substantial importance, especially in the Decision Tree and Random Forest models, thus indicating that favorable market conditions are crucial for entrepreneurship. Inclusive Government and Inclusive Culture had a relatively lower importance but still meaningfully contributed to the models, thus indicating that government policies and cultural factors, while secondary, do influence the entrepreneurial activity. Using Pandas and plotly.express libraries are used in python for geospatial analyses. The following world maps show the relative importance of feature variables towards entrepreneurial development across countries. As seen in Figure 4, North America, Europe, and some parts of Asia display higher footprints of inclusive resources. However, other regions of Africa and South America show moderate to low scale use of inclusive resources, thereby having a limited capacity of these resources. It means that the high

concentration in certain areas might correspond to better resource accessibility, infrastructure, or supportive policies. These resources that cover physical, financial, or institutional resources are necessary for IEE. The map seems to emphasize structural disparities globally, thereby revealing where resources are more impactful or better aligned with entrepreneurial activities. This is aligned with empirical evidence where micro-finance, venture capital, and government financial support in form of grants significantly boost entrepreneurial activities [71]. Inclusive financial access mitigates barriers faced by marginalized populations. However, high-performing regions (as shown on the map) highlight that they have robust financial ecosystems which enable early-stage entrepreneurship [3]. The regions with dominance of inclusive resources have a high level Information and Communication Technology (ICT) manifestation, thus projecting more innovation and low-cost nascent entrepreneurial activities [80]. Moreover, it is witnessed that the countries that invest in inclusive education platforms see an upsurge in entrepreneurial activity [81].

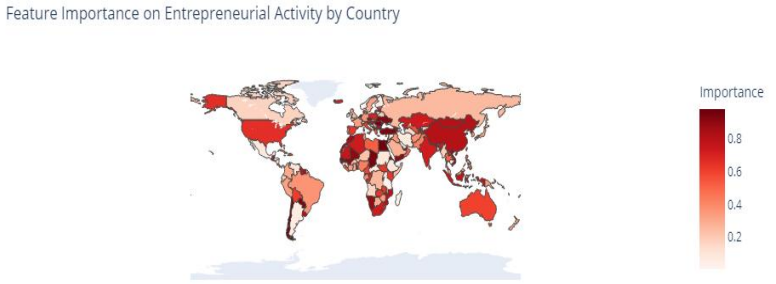

Figure 4. Inclusive resources.

*Note: Source: Authors' own elaboration using Python 3.7.12 (Plotly Express 5.24.1; Pandas 1.3.5; NumPy 1.21.6). Data compiled from: Global Entrepreneurship Monitor, GEM Global Report (2008–2020), https://www.gemconsortium.org/data; World Economic Forum, Global Competitiveness Report (2008–2020), https://www.weforum.org/publications/; Social Progress Imperative, Social Progress Index (2013–2020), https://www.socialprogress.org/social-progress-index. All sources accessed: March 2025.

Figure 5. Inclusive governance.

*Note: Source: Authors' own elaboration using Python 3.7.12 (Plotly Express 5.24.1; Pandas 1.3.5; NumPy 1.21.6). Data compiled from: Global Entrepreneurship Monitor, GEM Global Report (2008–2020), https://www.gemconsortium.org/data; World Economic Forum, Global Competitiveness Report (2008–2020), https://www.weforum.org/publications/; Social Progress Imperative, Social Progress Index (2013–2020), https://www.socialprogress.org/social-progress-index. All sources accessed: March 2025.

Figure 5 demonstrates the level of inclusive governance across regions. [82] demonstrated that inclusive institutions significantly influence the entrepreneurial entry rates, with a particular emphasis on how the governance quality affects opportunity-based entrepreneurship. The authors note that a one standard deviation improvement in inclusive governance can lead to a 20-40% increase in opportunity entrepreneurship. The map clearly shows that the darker red regions around the globe (indicating higher importance = 0.8) appear prominently in North America, Australia, and Russia. It shows that strong governance, political stability, and institutional support influence nascent entrepreneurial activities. South America and African nations depict moderate importance of inclusive governance support in these regions. Africa, south Asia, and some part of Middle East demonstrate lower importance, which may be due to certain challenges such as political instability and the lack of a regulatory environment. Finally the USA, Canada, and Germany have focused on development of inclusive governance, leading to stable EE.

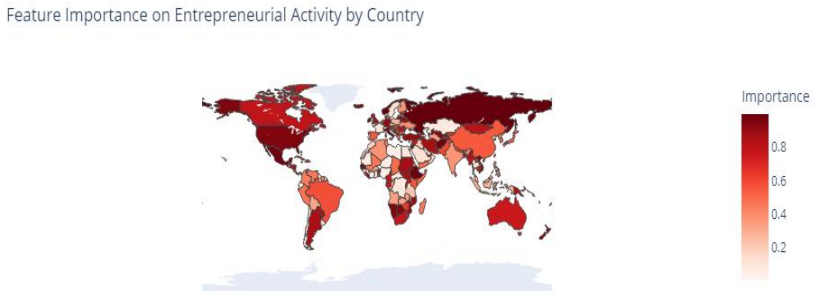

Figure 6. Inclusive culture.

*Note: Source: Authors' own elaboration using Python 3.7.12 (Plotly Express 5.24.1; Pandas 1.3.5; NumPy 1.21.6). Data compiled from: Global Entrepreneurship Monitor, GEM Global Report (2008–2020), https://www.gemconsortium.org/data; World Economic Forum, Global Competitiveness Report (2008–2020), https://www.weforum.org/publications/; Social Progress Imperative, Social Progress Index (2013–2020), https://www.socialprogress.org/social-progress-index. All sources accessed: March 2025.

Inclusive culture only promotes entrepreneurial development when there is diversity, social acceptability, and tolerance in a region (Figure 6). Inclusive culture with lighter shades (0.2-0.4) appear in some parts of Asia and Africa. Inclusive culture is supportive in North America and Western Europe because these regions have a higher tolerance for failure, strong collaborative networks, role models, and cultural acceptance to become entrepreneur [83]. Moreover, the cultural norms manifested in family businesses reflect high respect given to entrepreneurs that can be witnessed in the indigenous entrepreneurial activities [84]. Therefore, cultural values promote diverse ideas, social networking, and business collaborations that lead to successful entrepreneurial activities in a region.

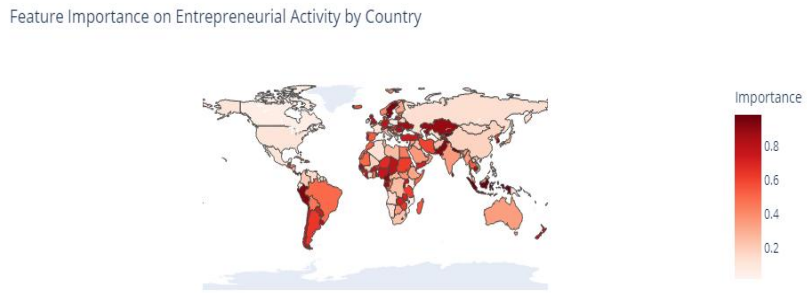

Figure 7. Inclusive markets.

*Note: Source: Authors' own elaboration using Python 3.7.12 (Plotly Express 5.24.1; Pandas 1.3.5; NumPy 1.21.6). Data compiled from: Global Entrepreneurship Monitor, GEM Global Report (2008–2020), https://www.gemconsortium.org/data; World Economic Forum, Global Competitiveness Report (2008–2020), https://www.weforum.org/publications/; Social Progress Imperative, Social Progress Index (2013–2020), https://www.socialprogress.org/social-progress-index. All sources accessed: March 2025.

Entrepreneurial success largely depends on market accessibility, financial inclusion, and friendly entrepreneurial policies (Figure 7). Inclusive markets can be witnessed in Africa and developing nations of Asia. Developing countries are adopting market accessibility policies to encourage marginalized communities to take active participation in entrepreneurial activities. Inclusive markets have been emerging in Latin America (Figure). Furthermore, cultural acceptance has been increasing in Latin America [57]. Due to shift in economic priorities, a shift from necessity to opportunity-based ventures have been seen. Social models of entrepreneurship are also receiving more attention by policy makers. This study reveals model predictability of inclusive features towards inclusive nascent entrepreneurial activities. The empirical evidence helpful for the policymakers to more accurately design an entrepreneurial development framework that boosts nascent entrepreneurship as the used framework to capture complex interconnected EE.

8. Discussion

The predictive analysis showed has shown the role of inclusive entrepreneurial activities to predict nascent entrepreneurial activities. Random forest, XGboost, and decision tree adequately predicted the entrepreneurial activities. Radom forest achieved a higher accuracy (80%) compared to the other models. For policymakers, the feature importance helps to prioritize the resources accordingly and provides a systematic way to optimize the entrepreneurial activities in a region. It means that providing quality education and information, enabling communication services and giving financial support are initial steps required by policymakers for nascent entrepreneurship. Second, focus must be shifted to governance related factors such as gender equality, government support programs, and effective government regulations. Then, inclusive culture practices should be focused where policymakers can encourage all communities to participate in entrepreneurial activities, which is possible by promoting gender equality and the freedom of expression. Additionally, they should work on market accessibility to all communities and they work on increasing domestic market size for optimizing local economic activities. Moreover, a geospatial analysis is helpful to understand the positioning of all inclusive ecosystem forces across the globe. This is helpful for countries to identify how they can boost nascent

entrepreneurial activities by focusing on the dimensions with low performances. The finding support with similar studies where ML models were used to predict entrepreneurial activities [67,85,89].

9. Future research

The applicability of these ML models could be applied across different economic contexts and EEs [8]. Second, the intersectionality of inclusivity factor should examine how gender, ethnicity, and socioeconomic status interact within entrepreneurial environments [57]. Moreover, it is important to understand the long-term impact of inclusive ecosystem interventions on sustainable economic development [3]. Conventional approaches have limitations in exclusively explaining the inclusive role of EE. In this regard, further empirical evidence opens new empirical insights for researchers and policymakers.

In this study, python based libraries were used to operationalize ML classification to Random Forest, Logistic regression, and XGBoost, and to predict IEE outcomes. Future research could use theoretical rigorous and alternative models for non-linear modeling such as Conic Multivariate Adaptive Regression Splines (CMARS), as well as the more advanced robust extension RCMARS [40,86,87]. Moreover, management and innovation frameworks could be used to explain human and organizational capital dimensions [88,89].

10. Conclusions

This study used factors of IEE to predict nascent entrepreneurial activities. The theoretical framework of an EE was tested to see the nonlinear association of underlying variables within the context of inclusiveness. First, the current research in the field of an IEE was extended by applying predicted ML models. Second, the outcomes of the predicted models can help policymakers to prioritize their efforts while taking entrepreneurial development decisions. Third, global footprints of nascent entrepreneurial activities were evaluated by taking input features of IEE. It was demonstrated that XGBoost and Random Forest perform better than decision tree determined through fine-tuning process, relevant AUC and model accuracy score. Random Forest had the best recall and AUC measurements, making it particularly useful in cases where identifying positives is crucial. However, XGBoost showed the highest specificity, meaning it is very effective at identifying negatives. Finally, all models followed mathematical equations to adopt algorithms and predict the accuracy.

In terms of feature importance, this study revealed that inclusive resources are the most influential factor across all models, followed by Inclusive Government, Inclusive Market, and Inclusive Culture. The policymakers could lever their efforts by focusing on this hidden pattern to achieve key strategic efficiencies. The fact that Random Forest assigned a higher importance to Inclusive Culture may indicate that this model captures cultural effects more effectively than the others. Policymakers can formulate entrepreneurial policies by aligning the inclusive factors according to their level of importance. Intuitively deploying inclusive resources is critical for success of startups. This analysis suggests that Random Forest may be the most balanced and effective model for this particular application, especially in scenarios where the correct classification of positive and negative cases is equally important. Additionally, the focus on Inclusive Resources should be central in any interventions or policy designs aimed at fostering entrepreneurial activity.

The findings provided practical insights for policymakers where they could use inclusive forces such as inclusive resources education, information and communication, quality of education, and financial services to promote entrepreneurial activities. Furthermore, political power of gender, government support, and inclusive government policies are considered important attributes. Inclusive culture includes the acceptance of all marginalized groups, and religion freedom, where inclusive

markets include market openness, market efficiency, and the dynamics of domestic markets. All these elements of the IEE configure in a certain way that promotes nascent entrepreneurial activities and reflects social implications for inclusive growth. In future studies, researchers could evaluate other advanced neural network models to improve the predicted accuracy of the model and theoretically test the nonlinear relationship among inclusive factors of entrepreneurial activities.

Author contributions

Conceptualization, K.H.; Data curation, Z.A.; Formal analysis, K.H. and T.O.B.; Funding acquisition, R.A.M.; Investigation, K.H. and Z.A.; Methodology T.O.B.; Project administration T.O.B.; Resources R.A.M.; Software Z.A.; Supervision T.O.B.; Validation Z.A.; Visualization K.H. and Z.A.; Writing – original draft, K.H.; Writing – review & editing, Z.A. and R.A.M.

Use of Generative-AI tools declaration

The authors declare they have not used Artificial Intelligence tools in the creation of this article.

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Conflict of interest

The authors declare no conflicts of interest.

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