Faculty of Business Economics

Master of Management

Master's thesis

International Market Selection and Entry Strategies: Discovering the Potential of A Machine Learning Approach

Hussain Ali

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Data Science

SUPERVISOR :

Prof. dr. Pieter PAUWELS

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ABSTRACT

In this hyper competitive landscape, companies are entering international markets. The key towards internationalization is market selection based on size, potential and attractiveness and enacting pertinent entry strategies. Traditional methods involved human judgements, lack of analysis, heuristics, follow the leader trap and were subject to biases and high inaccuracies. However, in this data revolutionized era, data-driven decision making is paramount. Technologies like AI, Machine Learning, Business Intelligence, Big Data analytics have changed the business landscape. Machine Learning is based on models learning from the past historical data. ML can be applied and reshape the conventional practices of IMS and MES. Various ML methods like supervised learning guided by target, reinforcement learning, unsupervised learning can assess market attractiveness based on past data analytics in seconds, predict market attractiveness for future or optimize currently enacted entry strategies like franchising, licensing, merger, acquisitions based on continuous learning approach. A sequential framework needs to be followed to incorporate machine learning to IMS and MES. With its million advantages like high accuracy, precisions, time saving, predictive analytics, efficiency and effectiveness; there are some challenges like data privacy concerns, unstructured data, quality concerns, resistance and integration constraints. However, advantages outnumber the challenges making ML optimized IMS and MES decision-making as the future for gaining competitive advantage.

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CHAPTER 1: INTRODUCTION

With the increasing trend of globalization, businesses are entering international markets to increase profitability and growth. For the firms seeking global expansion, market selection (IMS) and entry strategies (ES) play a crucial purpose. In fact, globalization is important for the firm's seeking growth and expansion. Businesses enter international markets for diversification, growth, global recognition, expansion and for finding new business opportunities. But these choices made have risks and have an prolonged impact on the overall firms' outcomes. (Islam et al., 2021). According to Agnihotri et al. (2022), IMS and entry modes to foreign markets have been the interest of researchers and choosing the appropriate mode has been and still is the most critical decision for international decision makers. Various entry modes such as importing, licensing, exporting, direct investment, JV, franchising and outsourcing are used by the companies wishing to enter foreign markets for growth and expansion (Buckley & Casson, 1998). Root (1998) emphasizes a structured approach for international market entry by discussing three market entry approaches based on risk exposures and level of control. Export-based market entry mode includes direct or indirect exporting with low-risk exposure and low control level, Contractual-based strategies such as licensing, franchising, management contracts, and technical contracts with moderate level of control and risk, and Investment-based strategies including joint ventures with high risk and level of control.

According to Root (1998), traditionally market entry decisions were based on managerial discretion and economic factors. These decisions were shaped by external factors such as the size of market, potential, competitive environment, cultural distance, political and economic stability and internal capabilities of the firm, where managers relied on experience and qualitative assessment to determine the best strategy. He further emphasized that managers often relied on heuristics to expedite the decision-making process where a firm might adopt a heuristic to enter markets with cultural similarities to its home country, in order to minimize the adaptation challenges. Buckley & Casson (1998) validate the claim by stating that initial market entry decisions were based on qualitative judgements and managerial intuition. Decision-making was largely guided by transaction cost economies and Dunning's eclectic paradigm before 1980s. During the 1980-1990s, with the emergence of structured decision models there was a shift towards comparative cost analysis. The period 1990s-2000s witnessed the introduction of multinational enterprise models incorporating factors like economies of scale, market imperfections and rivalry effects. Post 2000s era got revolutionized econometric models, multicriteria decision making models, tools like machine learning, big data analysis, AI and predictive analytics. Many entry mode decisions follow an effectuation approach, where lack of analysis and information made the leaders adopt less rational approaches based on gut feelings and intuitions (Ahi et al., 2016).

Moreover, market entry and selection were prone to lack of analysis in the past. Many companies enter new markets without thorough analysis, leading to uninformed decisions. As per Hilmersson et al. (2022), firms entering international markets often relied on improvisation making spontaneous decisions without proper analysis and based on business network commitments. In past, many firms entered international markets without rigorous analysis mainly due to time constraints, limited cognitive resources, lack of comprehensive data and analytical tools and cognitive biases. Resultantly, they expanded into too many markets and often failed. As Fasolo et al. (2024) confirms that it often leads to deleterious consequences such as excessive market entry.

Traditionally, problems associated with IMS were insufficient data and lack of a suitable decision-making method enabling firms to take a structured approach for IMS (Calof & Viviers, 2020). Moreover, IMS & ES relied on a combination of qualitative and quantitative research methods; utilizing macro-economic factors like GDP, industry reports, demographics; primary sources including personal interviews, observational research, case study, focus groups and limited data storage and analytics utilizing spreadsheet tools like MS excel. However, this was subject to limitations such as limited data availability, time and cost, highly subjective decision making and uncertainty. Marketeers had to collect data, determine if it is useful or not, create hypotheses, test, analyze and evaluate for selecting markets and designing the entry strategies which were subject to longer working hours (Yin, 2022).Companies used two methods in the past for IMS: A systematic approach which was subject to time consuming statistical analysis on collected data and a (prevailing) unsystematic approached characterized by informal, biased and overly simplified heuristics (Musso & Francioni, 2014). Both the approaches were subject to high risk of inaccuracy and uncertainty.

Another issue prevailed in the past was decision-making imitating the market leaders without proper analysis and strategic planning. Companies simply followed the trend where leaders entered certain market if their success would translate into their own. Vakratsas, Rao, and Kalyanaram (2003) found in their empirical studies that companies followed their leaders and frequently incurred market share penalties due to delayed market entry. Negative risks were found to be associated with imitating the market leaders during entry decisions without proper analysis and tailored strategy. The study by Parry and Bass (1990) confirms the validity where "follow the leader" approach without thorough analysis led to suboptimal results.

In this era of digitalization and big data, traditional approaches are becoming outdated and no longer sufficient to sustain long-term growth. As per Joel & Oguanobi (2024), in this hyper-competition, data-driven strategic decision making is paramount. With new technologies such as big data analysis, AI, BI, ML, predictive modelling and deep learning; businesses are in a better position to enter markets with high data accuracy, low level of uncertainty, high decision-making efficiency and sustainability. With the emergence of digital technologies, the model for business decision-making has revolutionized (Hervé, Schmitt, Baldegger, & Szambelan, 2020). These technologies utilize predictive analytics, modelling, historical trend analysis and stats based algorithms forecasting trends in future, identify potential risky markets and profit maximization for businesses (Joel & Oguanobi, 2024). Machine learning helps bring efficiency, accuracy and effectiveness by offering automated, data-driven alternatives to traditional approaches. Various machine learning techniques have revolutionized the decision-making framework. However, existing literature is limited on the integration of machine learning into IMS and ES process. Machine learning has a potential to revolutionize the IMS & ES and overcome the obstacles faced in the traditional approaches used. Various ML techniques can potentially be applied to the IMS for efficient decision-making. Supervised learning (SL) utilizing logistic models, classification algorithms, and regression analysis, Unsupervised learning (UL) techniques including cluster analysis, reinforcement learning and NLPs are widely used techniques in machine learning (Özkan-Okay et al., 2024).

To incorporate machine learning in market selection and entry strategies, a framework needs to be followed by firstly collecting the data, preprocessing and data transformation, training of algorithms, execution and evaluation (Falco et al., 2020). With a wide range of advantages by optimizing the market entry strategies with the help of machine learning, there are some challenges. With 70% of the data being collected from online platforms, they are subject to data quality challenges, data sparsity, unobserved phenomena, bias patterns, data heterogeneity and missing values (Hair & Sarstedt, 2021).

This paper contrasts the traditional market selection and entry strategies with advanced data-driven machine learning optimized approaches. Application of machine learning to market selection and entry is of little research so, this paper will discuss various machine learning techniques that can be used to optimize entry strategies and assess most attractive markets for entry based on existing literature and case study analysis. This research will outline the framework for the practical application of ML in IMS and entry strategies.

1.1 Problem Statement

Traditionally, IMS and ES relied heavily on heuristics, managerial intuitions, subjective judgments, follow the leader trap, expert analysis and key macroeconomic indicators. These methods are subject to human errors, cognitive biases, limitations arising from data insufficiency and inadequate analysis. Furthermore, they struggled to predict future market potential. While ML offers promising capabilities for data-driven IMS and ES performance, its application in this area remains significantly under-researched. Resultantly, there exists a knowledge gap how machine learning can address the inherent drawbacks of traditional IMS and ES approaches and enhance the precision effectively and efficiently.

1.2 Research Objectives

1. Compare and contrast the conventional IMS and ES methods with modern data-driven decision-making frameworks optimized by ML techniques and advanced analytics.
2. Identify the key challenges associated with traditional IMS and ES approaches such as heuristics, managerial intuition, inadequate analysis, data insufficiency, follow the leader trap and expert analysis.
3. Understand ML and its potential to present its capability in overcoming the existing barriers of conventional approaches.
4. Acknowledge the potential of key ML techniques such as SL to overcome the issues related to competitor imitation and inadequate analysis.
5. Understand ML techniques such as unsupervised learning (UL) to address issues related to heuristics-based decision-making, managerial intuition, and human evaluation.
6. Understand the role of NLP and data mining (DM) in overcoming the challenges associated with data insufficiency by extracting and mining relevant information from tons of unstructured datasets.
7. Acknowledge the potential of RL and adaptive learning models in improving the entry strategies (ES) based on active feedback mechanism.
8. Identify framework for the practical application of ML in IMS & ES decision-making.
9. Identify key challenges associated with the adoption of machine learning (ML)

1.3 Research Questions

1. What are the critical indicators of IMS and ES decisions?
2. What are the principal drawbacks of conventional approaches to IMS and ES?
3. How can ML mitigate the inherent limitations of the traditional methodologies such as reliance on heuristics, managerial intuition and gut feelings, “follow the leader”

effect and insufficient data analysis?

4. What ML tools can be applied for data-driven assessment and selection of international markets?
5. What ML models can be used to improve entry strategies (ES) and predict future outcomes efficiently?
6. What is a viable framework and what are the essential steps to implement ML in IMS and ES?
7. What key challenges associated with the adoption of ML in IMS and ES?

1.4 Significance of the Study

This research will be significant for both industry and academic researchers as the application of ML in IMS and ES is still under explored. In the past, IMS and ES faced significant problems due to heavy reliance on subjective judgements, heuristics, cognitive biases, gut feelings and intuition, insufficient analysis and "follow the leader" effect. However, ML has the potential to overcome all these problems. This research will guide future managers in this data-driven environment to improve strategic decision-making regarding internationalization. This paper will also give directions to future researchers to explore more models that can be used in formulating entry strategies and assess international markets. Moreover, this research will also offer insights for further exploration into the economic implications, implementation frameworks and potential obstacles associated with its adoption. This will give a systematic approach for firms wishing to enter international markets in a sequential way starting from problem identification, ML techniques, implementation and mitigation of challenges for less risky, highly certain and accurate decision making.

Table 1

Key Concepts and Definitions

Key Themes	Definition	Source
International Market Selection (IMS)	Strategic decisions by which companies choose the markets.	Buckley & Casson (1998); Root (1998)
Entry Strategies (ES)	Structured approaches through which firms establish a foothold in new markets.	
Franchising (FC)	Granting foreign firms operational rights.	
Licensing (LS)	Permitting foreign use of assets.	
Export (EX)	Selling domestic goods internationally.	Dunning, J.H. (1988); Buckley & Casson (1998); Root (1998)
Outsourcing (OS)	Contracting external firms for production/services.	
Direct Investment (DI)	Establishing operations in foreign market by the means of investment.	
Joint-Ventures (JV)	Shared ownership in foreign markets.	
Machine Learning (ML)	Machines learning from the data to make decisions.	Mitchell, T. M. (1997)
Supervised Learning (SL)	Learning by observing patterns from input such as market trends, consumer demand, purchase history.	Lewaaelhamd (2023)
Unsupervised Learning (UL)	Discovering patterns and insights without human supervision.	Naeem et al. (2023)

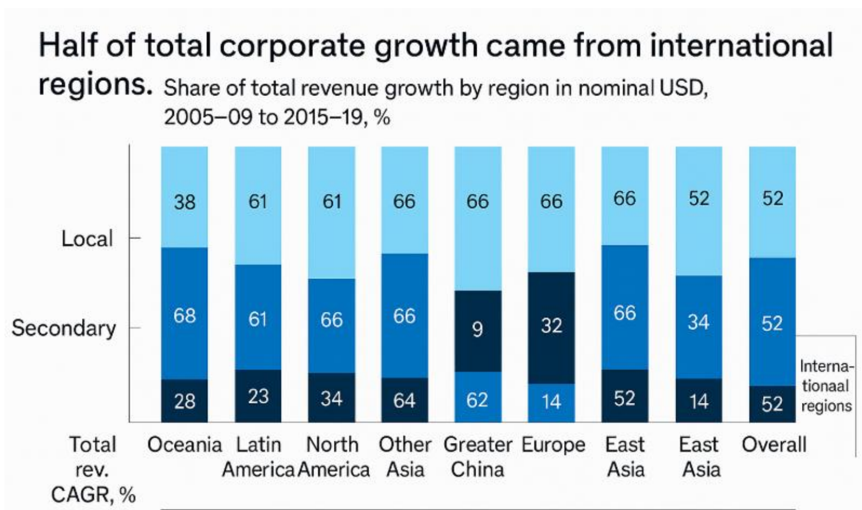
Decision Trees (DT)	Classifying based on characteristics such as historical trends, demand, size and demographics.	Manoharan et al. (2024)
Random Forests (RF)	Aggregating the output from decision trees by selecting the relevant features and excluding irrelevant.	Iranzad & Liu (2024)
K-means (K)	Advanced consumer segmentation using multi-criteria features.	Rafiei (2024)
Natural Language Processors (NLP)	Mining and deriving meaningful insights from varied unstructured sources such as reports, social media.	Shi (2024)
Reinforcement Learning (RL)	Adaptive learning model based on trial-and-error approach.	Murphy et al. (2022)

(Source: Created by the author, 2025)

CHAPTER 2: LITERATURE REVIEW

In this era of globalization, businesses are entering international markets to increase profitability and growth. Most of the companies' executives look beyond their home countries for growth. As per McKinsey & Company (2023), half of the corporate growth till 2019 came from foreign market expansion. Many European and Asian companies relied on international markets for growth perspective. As per illustrated in the graph below (Fig.2), a significant portion of the corporate revenue growth came from international regions, highlighting the importance of entering international markets.

Fig.1: Share of growth from region wise



(Source: The Expansion Code: Go International if You Can Beat Local Market, 2023)

For firms looking to expand globally, market selection and entry approaches are critical. In fact, internationalization is critical for businesses looking to grow and expand. Businesses enter overseas markets to diversify, grow, get recognition internationally, expand, and seek new business prospects. However, these plans are uncertain and have enduring impact on the firms (Islam et al., 2021).

2.1 International Market Selection

According to Agnihotri et al. (2022), IMS and entry modes to foreign markets have been the interest of researchers and choosing the appropriate mode has been and still is the most critical decision for international decision makers. IMS is a complicated decision because it requires firms to consider various factors such as economic, cultural and strategic. Johanson and Vahlne

(1977) introduced the UPPSALA model suggesting that the companies expand into international markets with lower psychic distance. According to this approach, the main emphasis is on experiential learning. According to the transaction cost theory by Williamson (1985) firms minimizes the risks associated with opportunism and uncertainty by selecting the international markets on cost-benefit analyses. Dunning's (1988) eclectic paradigm provides a framework for international market selection based on possession, geographical presence and global expansion factors. These location specific advantages considered by companies while entering international markets includes resource availability, economic factors, regulatory system and ease of doing business. According to Root (1998) in his book "Entry Strategies for International Markets", decision to enter international markets is influenced by external indicators such as the size of market, potential, environmental factors such as regulatory system, political and economic stability, geographic distance, cultural similarity and internal factors such as consumer demand, products and resources.

There are different modes a firm can enter international markets. These are explained below:

2.2 Market Entry Strategies

Root (1998) highlights a systematic approach to international market entry, outlining three alternative entry methods based on risk exposure and amount of control. Export-based market entry modes include direct or indirect exporting with low-risk exposure and control; contractual-based strategies such as franchising, managerial contracts, license rights and technical contracts with moderate control and risk; and investment-based strategies such as joint ventures with high risk and control. According to Barney (1991) in his resource-based view, strong companies with more resources, competitive advantage and high internal capabilities opt for high risk and high control modes like direct investment whereas weaker companies with mediocre resources choose joint-ventures.

Exporting is the process of producing in the home country and selling them in the international markets. It is one of the most used international market entry strategies. Due to reduced operational and fiscal risk, it enables the companies wishing to enter international markets with less exposure (Knight & Cavusgil, 1996). Licensing allows the companies to transfer their trademarks and intellectual property rights in exchange for royalties. This way companies can enter foreign markets with less financial exposure (Anderson & Gatignon, 1986). Franchising on the other hand is a strategy permitting the foreign use of assets by granting rights. JV occurs when two firms pool their assets consolidated with one legal entity (Kogut, 1988). However, this kind of setup requires effective management system and leadership in order to avoid conflicts over profit sharing and decision making. Lastly, high control and high risk foreign direct investment refers to the concept where an entity purchases an asset or company in a foreign country. However, this requires strong capabilities and financial position.

2.3 Challenges associated with the traditional approaches

Prior to the 1980s, decision-making for IMS & ES approaches had been profoundly affected by transaction cost economies and Dunning's eclectic paradigm. The introduction of structured decision models in the 1980s and 1990s marked a shift toward comparative cost analysis. The 1990s and 2000s saw the emergence of international enterprise models that included elements such as economies of scale, market inefficiencies, and competition effects. The post-2000 era saw the revolutionization of econometric models, multicriteria decision making models, and tools such as ML, big data analysis, AI, and predictive analytics. However, there were certain inherent constraints to outdated methodologies.

According to Root (1998), historically, market entry decisions were based on managerial discretion and economic criteria. External considerations influencing these decisions included market potential, competitive environment, cultural distance, political and economic stability, and the firm's internal capabilities, with managers relying on experience and qualitative assessment to decide the optimal plan. He added on to argue that managers frequently used heuristics to fast-track the decision-making process, such as entering markets with cultural resemblance to their home country to reduce adaption issues. Buckley and Casson (1998) support the idea by arguing that initial market entry decisions were made based on qualitative judgments and managerial intuition. Many entry mode decisions follows an effectuation approach, where lack of analysis and information made the leaders adopt less rational approaches based on gut feelings and intuitions (Ahi et al., 2016). Guercini and Milanesi (2022) study systematically reviewed 32 articles published during 1997 till 2021 focusing on the use of heuristics in IMS & ES. They claim that the use of heuristics in IMS decision making is still under researched.

However, the use of heuristics and managerial intuitions can lead to suboptimal outcomes. According to a research based on longitudinal case study analysis, the use of heuristics and managerial subjective judgments in international market decisions put marketers in vulnerable position (Guercini & Freeman, 2023). Many managers use cognitive shortcuts such as entering the markets like their home in terms of overall culture. According to Maitland and Sammartino (2014), they conducted 17 in-depth interviews and found managers often faced complexity and uncertainty in decision-making when they applied mental shortcuts instead of extensive market analysis. Traditionally, entry mode decisions guided by managerial experience and gut feelings were influenced by their past working experience in foreign countries, perceptions of competitor’s strategic moves and international news. However, this often led to inadequate decisions (Aharoni et al., 2010). Managerial intuition and heuristics in decision-making can lead to biases that result in overconfidence, heavy reliance on past success and negligence on key factors such as consumer preferences and macroeconomic factors. Overconfidence often leads the companies to underestimate entry barriers and overestimate the ability to adapt to new markets, resulting into strategic failures and financial strains (Tversky & Kahneman, 1974).

Moreover, market entry and selection were prone to lack of analysis in the past. Traditionally, firms heavily relied on heuristics, managerial institutions and business networks rather than thorough analysis (Root, 1998; Buckley & Casson, 1998). Many businesses enter new markets without conducting thorough research, resulting in uninformed decisions. According to Hilmersson et al. (2022), enterprises entering international markets frequently relied on improvisation, making rapid assessments without sufficient analysis and depending on business network commitments. Historically, many corporations entered global markets without conducting thorough analysis, owing to time constraints, limited cognitive resources, a lack of comprehensive data and analytical tools, and cognitive biases. As a result, they expanded into too many markets, often failing. As Fasolo et al. (2024) corroborate, it frequently results in negative repercussions such as excessive market entrance.

Lack of analysis often leads to the risk of failure in international expansion. As per Rahman et al. (2017) in their case-study approach-based research on 212 Bangladeshi SME firms, small and medium sized firms when entering foreign markets encountered economic obstacles like limited market knowledge, insufficient financial resources, and inadequate data. This often led them to enter international markets without thorough analysis and resultantly the likelihood of failure increased. Islam et al. (2022) also contributes to our claim that lack of analysis on key macro-economic factors such as attractiveness, concentration and density often led to failures in timing the entry to international markets. Another study by Ahi et al. (2016) on 6 SMEs based in Finland claims that while making international market entry decisions, there has been significant lack of analysis in decision-making in practice. This is mainly due to resource constraints, managerial experience and intuition, lack of formal decision-making processes, information gaps and perceived urgency. Horn et al. (2005) emphasized cognitive biases and flaws in decision-making to enter international markets where lack of thorough analysis often led to overestimating market size and potential, underestimating competition and ignoring potential risks.

Historically, other issues associated with foreign market selection were insufficient information and missing a suitable framework for decisions that would enable them to take a comprehensive approach to international market selection (Calof & Viviers, 2020). Root (1998) emphasizes that firms frequently lack access to key market indicators such as market trends, competitive analysis and consumer insights which are crucial for informed decision making. Market selection and entry strategies were based on a mix of quantitative and qualitative research methods, including macroeconomic factors such as GDP, industry reports, and demographics; primary sources such as personal interviews, observational research, case studies, and focus groups; and limited data storage and analytics using spreadsheet tools such as MS Excel. However, this was constrained by factors such as data availability, time and expense, highly arbitrary decision making, and unpredictability. According to Choudhury et al. (2023), statistical data collection methods dominated the 1950s and 1960s, while the 1970s and beyond exposed the secrets of big data. However, the biggest challenge was a lack of data storage technologies such as spreadsheet software, predictive analytics, time and cost, restricted data availability, uncertainty, and future forecasts resulting in failures and future disasters. Cavusgil et al. (2014) highlighted the key issue supporting our claim that lack of data often led the firms to base their market entry decisions on broad generalizations. As a result, decision-making was based on speculative information and subjective evaluation. Watson et al. (2018) examines historical firms on relational approaches for market selection and entry strategies based on developing networks and personal relationships. But this approach constrained huge data sets and insufficient knowledge to enter international markets.

Marketers had to collect data, determine whether it was valuable or not, develop hypotheses, test, analyze, and evaluate for choosing markets and devising entrance strategies all while working longer hours (Yin, 2022). Companies have previously used two approaches for international market selection: a systematic approach that involved time-consuming statistical analysis of collected data and a (prevailing) unsystematic approach characterized by informal, biased, and overly simplified heuristics (Musso & Francioni, 2014). Both approaches carried a substantial risk of error and uncertainty. Cognitive biases such as availability heuristics and availability heuristics impacted the decision-making process adversely where decision makers where they simply focused on the information that supported preconceived notions and simply ignored the contradictory data (Papadopoulos & Martín, 2011). Traditionally, many companies in the past entered international market with lack of information and based on the assumption that a similar product performed well in another market, only to find that market dynamics were different.

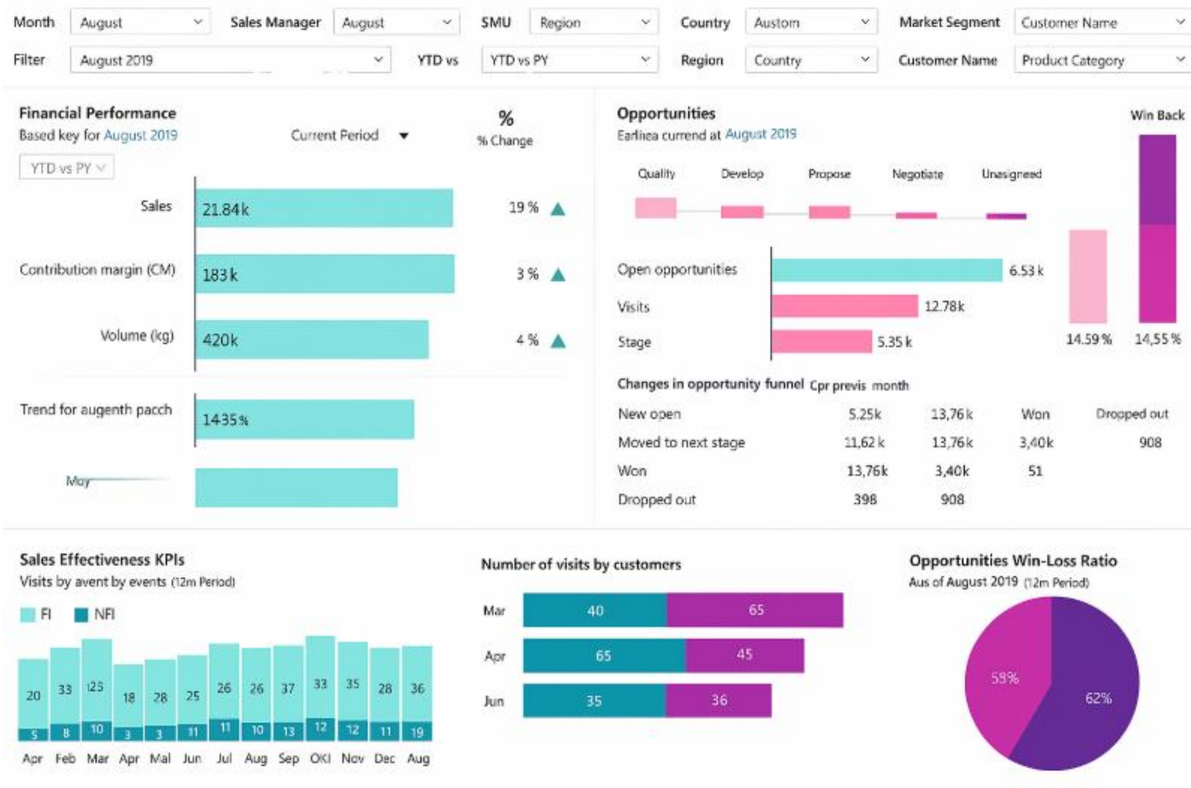
Finally, in the past, decision-making was based on imitation of market leaders rather than proper analysis and strategic planning. Companies just followed the trend of leaders entering specific markets, expecting that their success will convert into their own. Vakratsas, Rao, and Kalyanaram (2003) discovered in their empirical investigations that corporations followed their leaders and frequently suffered market share losses because of delayed market entry. This "laggard" market entry strategy often occurred in the past where companies waited for the leaders to establish first in the new market and only upon their success, attempted to replicate by entering the same market. Negative risks were found to be associated with imitating the market leaders during entry decisions without proper analysis and tailored strategy. The study by Parry and Bass (1990) confirms the validity where "follow the leader" approach without thorough analysis led to suboptimal results. Another study by Lu (2002) on 1194 Japanese subsidiaries in foreign markets also validated that companies try to imitate the entry modes of earlier entrants without thorough independent analysis which led to adverse impacts. Gentry et al. (2013) study on startups claim that they try to imitate the entry decisions of similar firms which lead to failed performance, early exists and overcrowded markets. Indeed, following the leader footsteps without analyzing your own capabilities and market analysis can lead to adverse impacts. For instance, if McDonald's decides to enter Chinese market and succeed doesn't mean Burger King will get the same success if they follow the footsteps of McDonald's by entering China as well.

In Essence, traditional approaches were obstructed by heavy reliance on heuristics, managerial intuition, gut feelings, insufficient data, inadequate analysis and "follow the leader" effects, leading to significant analytical gaps. The resultant failures led to neglected market insights, trends, dynamics, overconfidence and overestimation, highlighting the need for robust data-driven approaches.

2.4 Data driven approaches to International Market Selection and Entry Strategies

In this era of digitalization and big data, conventional approaches are becoming obsolete and insufficient to sustain long-term success. As per Joel & Oguanobi (2024), in this hyper-competition, data-driven strategic decision making is paramount. As per Böringer et al. (2022) in McKinsey report, data-driven decision making is enhancing the current landscape of corporate digital transformation. Companies leveraging data-driven approaches report 15-25% increase in their EBITDA. Instead of relying on intuition-based decision-making, data-driven dashboards leveraging predictive analytics and the use of big data makes decisions on real patterns rather than assumptions. They serve as a unified data reporting tool consolidating the key performance indicators for the international entry, future predictions on market success and entry strategies effectiveness as shown in the figure below:

Fig. 2: Analytics Dashboard Utilizing ML



(Source: McKinsey & Company,2022)

With new technologies such as big data analysis, AI, BI, ML, predictive modeling, and deep learning, businesses are better positioned to enter markets with high data accuracy, low uncertainty, high decision-making efficiency, and sustainable practices. With the introduction of digital technologies, the architecture of corporate decision-making has evolved. (Hervé, Schmitt, Baldegger, & Szambelan, 2020). As per Liu et al. (2025), digital technologies such as analysis of big datasets, predictive analytics, iOT and cloud-based computing systems have outclassed the traditional marketing models. These technologies use predictive analytics, modeling, historical trend analysis, and statistical algorithms to forecast future trends, identify potential risk factors and markets, and maximize profits for enterprises.

(Joel & Oguanobi, 2024). These technologies have the potential to overcome the inherent limitations of IMS and entry. The focus of this research will be on machine learning (ML) models as discussed below:

2.5 Machine Learning (ML)

Machine learning helps bring efficiency, accuracy and effectiveness by offering automated, data-driven alternatives to traditional approaches. According to Zhou (2021), ML is a technique that empowers systems to learn and develop by leveraging practical experience without the need of explicit programming. Various machine learning techniques have revolutionized the decision-making framework. According to exploratory research involving datasets on Dutch SMEs, machine learning (ML) has the potential as a predictive tool to inform decision-making through predictive analytics, exploration of hidden insights, market trends in international business (Bosma & Van Witteloostuijn, 2024). Machine learning (ML) can bring accuracy, precision, efficiency and effectiveness to the traditional decision-making process. As per Shrimali (2024), globally 49% of the organizations are using machine learning (ML) in marketing decisions with accuracy forecasting market insights up to 60%. It can be incorporated into decision-making for IMS & ES leveraging the advanced models and predictive analytics to explore market characteristics such as size, potential, macroeconomic factors like regulatory environment, economic stability and competitive landscape.

However, existing literature is limited on the integration of machine learning into international market selection and entry process. Various sources such as Scopus, EBSCO; journals like journal of international marketing, journal of research in marketing, journal of international business, journal of data science were explored in this research using Boolean operations such as AND, OR with search terms such as "Machine Learning", "International Market Selection", "Market Entry" were explored; however, limited research was found on the integration of ML into IMS and ES. It has a potential to revolutionize the IMS and overcome the challenges faced in traditional approaches used. Menzies et al. (2024) supports our claim highlighting the potential of machine learning in shaping forecasted market trends predictions and supporting strategic planning, which is crucial to international market selection and entry. However, many companies are still in the process of adopting machine learning into corporate decision-making. According to Hsieh et al. (2020), ML has the potential to revolutionize international expansion. They developed a model based on capabilities of the organization i.e assets, resources, market attractiveness and customer characteristics and applied machine learning approach enabling the analysis of these factors to surpass the traditional approaches efficiently. As per research, machine learning is proving useful for identifying market segments which is crucial preliminary step in market selection but segmentation alone does not determine which markets to enter and what entry strategies to implement. There is a need for research on how it can be effectively integrated into comprehensive market selection and entry strategies (Rey-Blanco, Arbués, López, & Páez, 2024). As per Shrimali (2024), 42% of the companies are still exploring machine learning and planning to leverage it in their decision-making framework.

Various machine learning techniques can be applied to the IMS for efficient decision-making. Supervised learning (SL) utilizing logistic regression, classification mechanisms, and regression analysis. Unsupervised learning (UL) techniques including cluster analysis, reinforcement learning and NLPs are widely used techniques in machine learning (Özkan-Okay et al., 2024). These techniques can overcome the inherent limitations of traditional approaches. Some of these techniques are explained below in relation to international market selection and entry strategies:

2.5.1 Supervised Learning (SL)

Supervised learning technique is a phenomenon in ML where algorithms learn from the training data to make predictions and classifications (Zhou, 2021). Supervised learning techniques can be used in international market selection and entry. According to Hsieh et al. (2020), supervised learning (SL) can analyze factors such as market prospects, legal frameworks, social factors, political conditions and economic metrics using labelled datasets and provides the companies wishing to enter international markets actionable insights into which market to target. Supervised learning facilitates predictions, anomaly detection and classification by training with the historical data such as patterns, buying records, engagment and customer behaviours (Lewaaelhamd, 2023). Another study applied supervised learning using K-means clustering and Support Vector Regression to segment travelers relying on real data and automated analysis (Alsayat, 2022). This can be applied to market selection and entry by classifying markets into high potential, low potential based on past data such as GDP, ease of doing business, customer demand, cultural similarity and company as the inputs for model training. It can overcome the limitations related to heuristics, cognitive biases, managerial intuitions, inadequate analysis and "follow the leader" effect with no independent analysis by identifying markets on real patterns and data rather than assumptions.

Decision tree (DT) algorithm comes under supervised learning (SL) that is used for regression analysis and classification purposes (Zhou, 2021). Decision trees divide the consumers into clusters based on their key traits such as consumer historical data, buying behavior, browsing logs and demographics (Manoharan et al., 2024). Aouad et al. (2023) introduced novel market segmentation trees integrating segmentation and response modelling for personalized decision-making. This study demonstrated that decision trees can increase the accuracy of market segmentation by identifying hidden patterns rather than relying solely on demographic and macro factors. Based on these attributes, the data can be divided into various groups for the purpose of identifying lucrative markets to penetrate.

Furthermore, random forest is a strategy that ensembles multiple decision trees and averages their output to increase classification accuracy. A key feature of random forests is the feature selection identifying the relevant features in the statistical model and excluding the non-relevant features (Iranzad & Liu, 2024). To support this, random forests, as reported by Duarte et al. (2022), use several decision trees within a bagging framework, splitting and averaging labels to construct a more balanced and accurate prediction model. It solves problems related to recommender systems, market forecasting and segmentation. Moreover, this helps to overcome the reliance on a single strategy by recommending the optimal market to enter based on the market options supplied by decision trees. So, decision trees help to classify possible markets based on historical data, ease of doing business, macroeconomic considerations, competition, and consumer demand, whereas random forests help to select the best market by combining decision tree insights. However, the research on the application of supervised learning into international market selection and entry is limited in the following journals: Journal of International Marketing, Journal of Research in Marketing and International Marketing Review, Journal of International Business and Journal of Strategic Management.

2.5.2 Unsupervised Learning (UL)

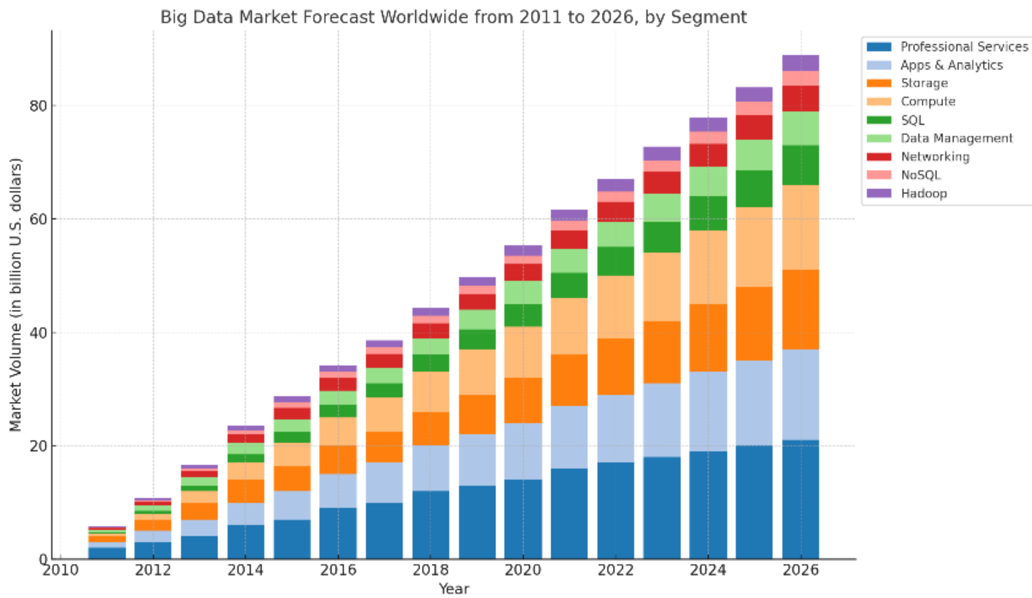
Unsupervised learning is a framework that where algorithms learn from unlabeled data (Zhou, 2021). Unsupervised learning identifies patterns and insights without human supervision (Naeem et al., 2023). Unsupervised learning, specifically clustering techniques like hierarchical clustering and K-means provides a solution for identifying international markets based on actual patterns rather than heuristics and subjective judgment. They help decision makers make decisions based on real data patterns. According to Rafiei (2024), advanced consumer segmentation utilizing clustering algorithms like K-means in big data can assist firms identify separate markets based on multi-dimensional characteristics. Another scholarly article by Ezenkwu et al. (2015) highlights the importance of an automated approach to segmentation utilizing big data and ML techniques such as clustering using unsupervised K-means mechanism and SOM. According to the research, Machine learning has led to widespread adoption of automated consumer segmentation, replacing ineffective conventional industry analyses, particularly for large data. These decisions bypass the limitations of heuristic-based decision making. Raja and Raja's (2025) study support this assertion by using K-means clustering to segment consumers based on actual data-driven variables including income, spending patterns, demographics, and culture, rather than subjective opinion.

Traditional methods also fall short of adaptation and agility when dealing with large data sets. K-means and deep learning techniques eliminates subjective judgments by depending solely on statistics and not only brings accuracy to segmentation but optimize marketing strategies based on actionable insights (Sharma et al., 2022). Hicham and Karim (2022) show that unsupervised mechanisms like K-means and DBSCAN improve segmentation accuracy, leading to better foreign market entry approaches. K-means clustering can be effectively applied to IMS and ES. These models can assist in data-driven market segmentation, uncovering hidden market patterns and insights facilitated by real data instead of assumptions, optimize the entry strategies based on the characteristics of clustered markets and predict future success.

2.5.3 Natural Language Processor (NLP)

Historically, a significant challenge in IMS and ES was data scarcity. Conventional approaches often relied on fragmented datasets and incomplete market intelligence which led to suboptimal decision making. However, Natural Language Processing has the potential to overcome this issue. Lack of data was a key issue in past. Data scarcity makes it difficult to assess decision making. A study by Zhou et al. (2012) based on 300 survey collected data on senior managers in China emphasizes that absence of relevant market data in conventional times led firms to misjudge consumer preferences and target market dynamics leading to suboptimal outcomes. However, current era is revolutionized by Big data. Big data defined as a shift from small databases to vast unstructured datasets (Mayer-Schönberger & Cukier, 2013). Nowadays, we have vast sources of data such as social media, websites, customer reviews, electronic magazines, journals, electronic trade reports and articles. These vast datasets include information about market trends and characteristics, consumer preferences, macroeconomic factors, demographics and cultural shifts. The key direction here is to utilize the unstructured data sets to inform decision-making in the most accurate and precise way. According to Adewusi et al. (2024), big data has revolutionized the way firms obtain, process and utilize data for precise decision-making. Big data has emerged as the main factors for the companies to get competitive edge (Ochuba et al., 2024). As per a report by Forbes, big data is estimated to make up to 80% of the enterprise data (Kennedy, 2024). Another report published in the Forbes estimates big data market forecast up to 85 Billion USD by 2026. They are projected to grow at CGAR of 15.5% with majority of its utilization in launching new products and transforming businesses for future (Columbus, 2018).

Fig. 3: Big Data Market Forecast Segment Wise



(Source: Forbes, 2018)

NLP has the potential to overcome the challenges of data scarcity in IMS & ES by utilizing big data. NLP is a branch of AI utilizing machine learning extract data from unstructured resources (Zhou, 2021). It enables the extraction from unstructured resources such as newspaper, social media, reports, articles, consumer reviews to inform decision-making. Shi (2024) found that NLP and text mining algorithms are used to assess financial disclosures from unstructured data sources like financial reports and social media posts, generating important information. Another study by Alantari et al. (2021), ML based sentiments extracted from unorganized channels such as customer reviews, social media and reports. It helps overcome data scarcity by leveraging AI-driven models and NLP automatically extracting information from big data sets. Decision related to international market selection and entry can be guided by accurately with the help of NLP.

2.5.4 Reinforcement Learning (RL)

The concept of reinforcement learning was first described by Sutton and Barto (1998) as the mechanisms that discovers what to do based on trial-and-error approach. Reinforcement learning is a data science method that employs algorithms that learn by trial and error and respond to feedback to improve results, rather than solely depending on past data to make predictions (Murphy et al., 2022). Reinforcement learning is being applied in marketing using self-learning mechanisms to recommend the best strategy based on preferences and market insights (Sivamayil et al., 2023). The assertion that reinforcement learning techniques can be used to determine the best strategies by examining resource allocation, pricing, demand planning, competitive dynamics, and production dynamics is supported by another study by Chodura et al. (2011) that was based on production companies.

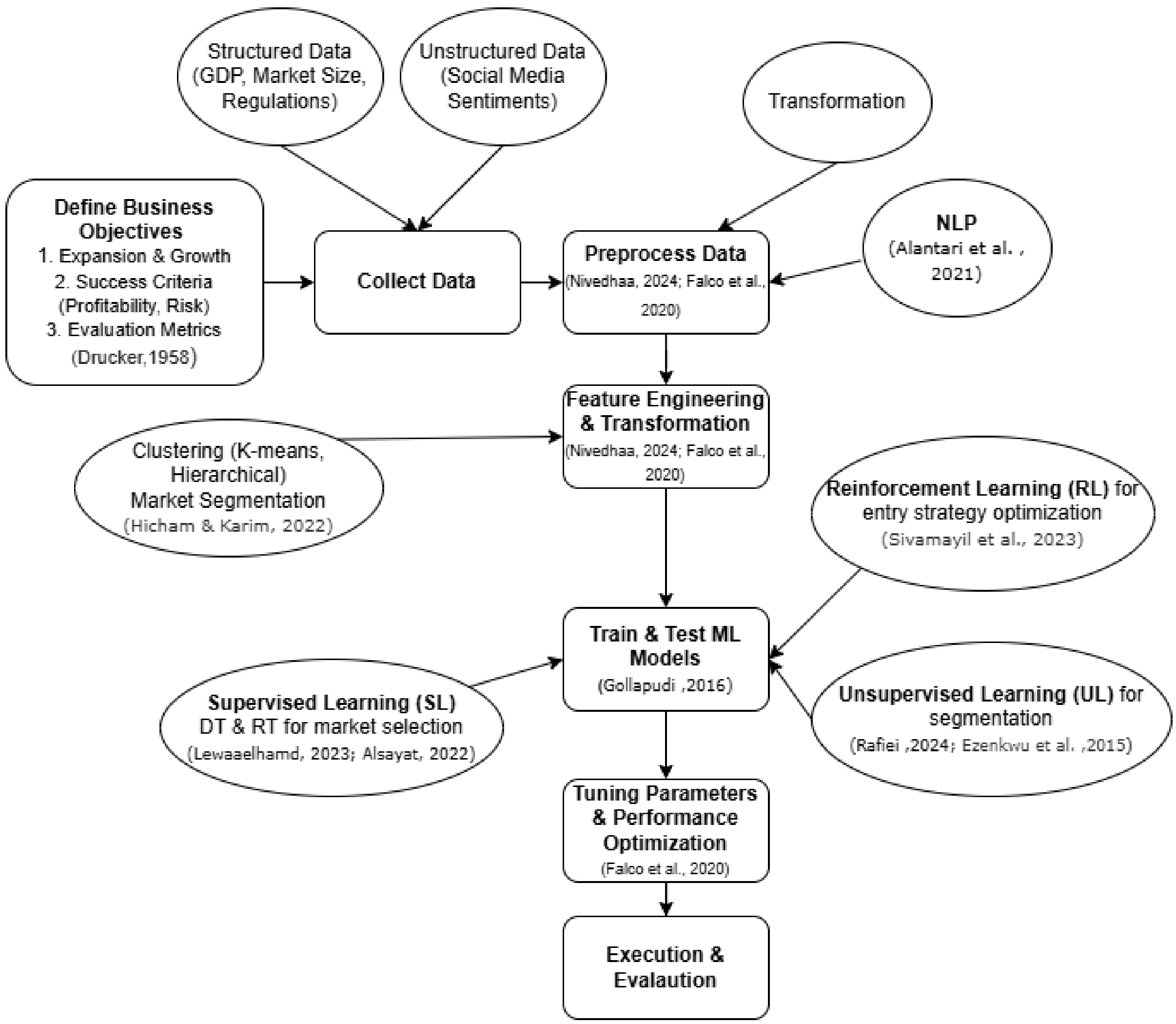
The ability of adaptive learning models to constantly improve market entry methods based on performance feedback and changing data can be applied to foreign market selection and entry approaches like franchising, licensing, exporting, partnerships, direct investment, and mergers. This claim is supported Kalra (2023) highlighting the effectiveness of market entry strategies in this rapidly changing market relies on monitoring, adaptation, continuous learning and consumer feedback. These advanced algorithms have the potential to improve entry strategies such as exporting, franchising, licensing in response to fluctuating market dynamics. They embed iterative learning models to swiftly adapt new market trends, regulations and policy effects into current strategies to improve them. However, the literature is limited on the integration of reinforcement learning in market selection and entry highlighting the opportunities for future research.

2.6 Framework for integrating ML in International Market Selection and Entry Strategies

To incorporate machine learning (ML) in IMS and ES, there needs to be a framework. This framework can act as the guiding map for future managers wishing to enter international markets. A framework has been developed by Falco et al. (2020), starting with data collection, preprocessing, training, testing, execution and evaluation. This research aims to develop a novel model building upon from the framework of Falco et al. (2020) tailored for IMS & ES. The first step is defining business objectives for the companies wishing to enter international markets. As Drucker (1958) in his book "Business Objectives and Survival Needs" emphasized that businesses need to identify why they want to expand, what are the key success criteria such as profitability, risk assessment and finally setting the evaluation metrics to perform well. The next step is going to be data collection. Data can be collected from structured sources such as trade reports or unstructured sources such as social media.

Now, machine learning will be incorporated to improve market selection and entry process. NLP helps to extract useful insights from the unstructured sources (Alantari et al., 2021). However, this data needs to be preprocessed to remove any missing values (Nivedhaa, 2024). So, it goes through transformation. After that, models are trained and test. Here, we can utilize machine learning to improvise international market selection and entry approaches. Different models such as supervised learning (SL) utilizing decision trees (DT) and random forests (RT) can be used for market selection (Lewaaelhamd, 2023; Alsayat, 2022); unsupervised learning (UL) models such as K-means for clustering (Rafiei, 2024; Ezenkwu et al., 2015) and reinforcement learning (RL) for entry strategy optimization (Sivamayil et al., 2023). After the testing and training of models, we can finally tune the parameters (Falco et al., 2020). Last step would be execution and evaluation for key improvements. The framework developed is given below in Fig. 4:

Fig.4: ML Implementation Framework



(Source: Created by the Author, 2025)

2.7 Challenges associated with ML adoption

With numerous advantages, there are some challenges associated with the adoption of machine learning in international market selection and entry. Some of these challenges are listed below in table 2:

Table 2

Challenges with Machine Learning

Challenge	Relevance to the research	Source
With 70% of the data being collected from online platforms, they are subject to data quality challenges, data sparsity, unobserved phenomena, bias patterns, data heterogeneity and missing values.	Data quality is the key to decision-making in IMS & ES.	(Hair & Sarstedt, 2021)
Deployment time for machine learning models such as SL, UL, RL and NLP can take up to 90 days while 18% of the firms even take longer making deployment a significant barrier to adoption.	Timely decision making has a significant impact on the firms entering international markets.	(Paleyes et al., 2022)
Machine Learning (ML) models helps in prediction accurately but does not help marketers to understand the reason of decision.	Lack of reasoning critically impacts the decision-making process in understanding why certain market or certain strategy is optimal under specific circumstances.	(Herhausen et al., 2023)

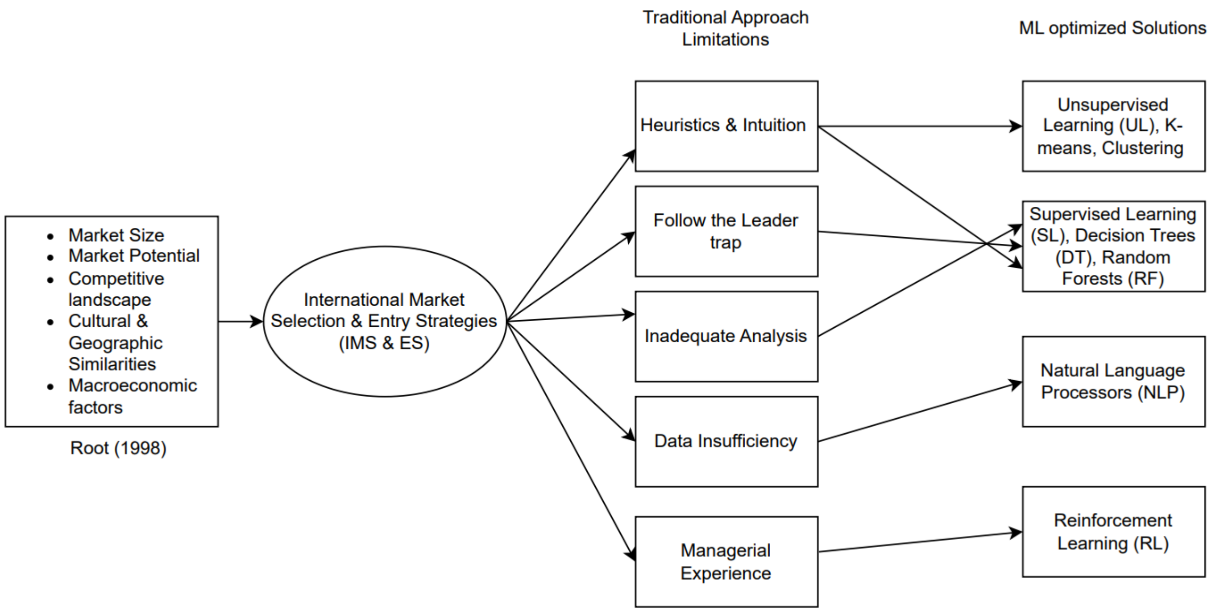
Machine learning (ML) models utilizes a probabilistic approach using the patterns of past data to make predictions which leads to different levels of uncertainty in the outcomes.	Prediction and uncertainty can lead to risky outcomes when entering unfamiliar markets.	(Herhausen et al., 2023)

(Source: Created by the Author, 2025)

Despite these challenges, studies highlight the potential of ML in shaping the landscape of market selection and entry. However, existing literature remains limited integrating machine learning to international market selection and entry approaches, highlighting directions for future research.

Based on the review of literature, this research paper comes up with the following conceptual framework as shown below in 2.8:

2.8 Conceptual Framework



(Source: Created by the Author, 2025)

CHAPTER 3: METHODOLOGY

This study describes the approach to investigate how top decision-makers such as C-suite, Management prospect the integration of machine learning (ML) into the international market selection (IMS) and entry strategy (ES). A qualitative, exploratory approach was selected examining the complex, under-theorized, context-sensitive nature of the study. The research aims to investigate rather than empirically test hypotheses or solve; a qualitative, exploratory design has been found the most suitable approach.

3.1 Justification for Methodological Choice

The choice of qualitative approach as the primary data collection method is justified in several key considerations:

1. **Exploratory Context of the Study**: The current literature does not fully portray the function of machine learning in international market selection. In these scenarios, qualitative interview approach is particularly useful because open-ended discussion can uncover hidden insights and viewpoints (Doz, 2011; Welch & Piekkari, 2006).

2. **Focus on Human Judgement and Interpretation**: Decisions about entering new markets are primarily based on human experience, judgment, and interpretation. It is difficult to simplify these aspects to quantitative factors (Root, 1998; Cavusgil & Zou, 1994).

3. **Lack of Structured Variables**: Systematic measurement scales are lacking for the integration of machine learning (ML) tools into international market entry (IMS & ES), in comparison to well-established concepts in international marketing (such as export intensity and psychic distance). This encourages the use of flexible, iterative, open-ended, semi-structured interviews.

4. **Focus on Reasoning, Contradictions and Hidden Insights**: Interviews have a notable ability to reveal precise, context-sensitive insights that would be concealed by surveys or secondary data, such as conflicts, patterns discovered, tensions, and strategic trade-offs.

3.2 Research Design

The current research uses a qualitative, exploratory research approach to find out how top decision-makers view the function of machine learning (ML) in decisions regarding the entrance into foreign markets. A quantitative method or deductive approach would not be adequate as the central research question seeks to explore a rather under-theorized field (Welch et al., 2006; Eisenhardt, 1989).

Particularly where cognitive, cultural, experiential, and technological dimensions merge, qualitative research helps to better understand how decision-makers view and reason through difficult market entry decisions. Especially in developing fields involving technology and digital transformation, this strategy match with demands in the international business literature for more theoretical pluralism and circumstantial depth (Sinkovics & Alfoldi, 2012; Nambisan et al., 2019).

The main goal of this research is to generate themes, uncover hidden patterns, blind spots and understandings of ML adoption in the internationalization process, so establishing the applicability of an open-ended semi-structured, in-depth interview method. This helps not to validate a hypothesis. This study intends to investigate how strategic decision-makers such as Owners, CEOs, founders, managers view and potentially include ML into their internationalization choices, not to create or empirically support a model. Instead of using ML techniques or existing frameworks, this exploratory qualitative research intends to understand by the deep insights.

The first step is literature review analysis, followed by thematic analysis with codes and sub-themes and finally, framework for the integration of ML in IMS & ES is developed by building machine learning models using KNIME Analytics platform. The details of methodology strategy are given below in table 3:

3.3 Research Strategy Overview

Table 3

Research Strategy Overview

Element	Specification
Approach	Qualitative, Exploratory
Method	Literature Review Analysis, In-depth, open ended semi-structured interviews, pattern analysis, thematic coding, ML framework

	development
Participants	Senior decision-makers (CEO, Founders, Directors, Managers) in internationalization, purposive and snowball sampling
Sample Size	9
Interview Duration	30-60 minutes
Mode	Hybrid approach, In-person and online (zoom, teams, google meets)
Interview Recording	Audio recorded with informed consent, Apple advanced audio coding
Transcription and Analysis	Manual and software aided (NVivo)
Analysis Framework	Thematic Analysis with sub-themes
Additional Tools	Profile statistics, keyword frequency analysis, Hidden Patterns Analysis, Thematic Distribution Insights
ML Framework	Data Collection, Pre-processing, training (Supervised, Unsupervised, Reinforcement) models, evaluation
ML Framework Tools	KNIME Analytics Platform, Python
Validation Strategy	3-tier validation using Literature, Thematic codes and interview quotes

3.4 Analysis Plan

The analysis plan is divided into three categories which are given below:

3.4.1 Literature Review Analysis

This study focuses on analyzing scholarly articles in three primary domains: International Market Selection (IMS), Entry Strategies (ES) and Machine Learning (ML). Top reviewed journals were selected such as Journal of International Marketing, Journal of International Business Studies, International Marketing Review, International Journal of Data Sciences, and Strategic Management Journal. Databases used were Google Scholar, JSTOR, Science Direct. Boolean Operations used were "AND" and "OR" with keywords such as International Market Entry, Entry Strategies, Heuristics, Decision-Making, Market Selection, Intuition, Experiential Decisions, Leadership footsteps, Data-Driven Decision-Making, Data Analysis, Analytics, Machine Learning, Supervised Learning, Unsupervised Learning, Natural Language Processors, Reinforcement Learning, and Model Training.

An initial pool of 204 scholarly articles was generated but it was narrowed down to 75 that were highly relevant to the core theme. Analyzing comprehensively scholarly articles and models by Barney, Root; the research was categorized across five major clusters: International Market Selection, Entry Strategies, Traditional Approaches to IMS & ES and associated limitations, Data-Driven Decision Making & Machine Learning (ML), and ML Challenges. This helped to develop two frameworks: Framework identifying external and internal factors for market selection and entry, limitations associated with traditional approaches and their ML optimized solutions; Framework for the application of ML in IMS & ES.

3.4.2 Thematic Analysis

9 in-depth open ended semi-structured interviews were conducted from top decision makers including CEO, founders, directors, managers. Interviews were conducted keeping in mind ethical considerations both online and in-person via platforms such as google meets, teams and zoom. A consent form was signed by all 9 participants. Interviews were on average between 30-60 minutes and recorded via informed consent. Purposive and Snow-ball sampling methods were used targeting the profiles that met the following criteria:

1. Senior-level participants such as CEOs, Founders, Presidents, Directors, Managers who were strategically responsible for International Market Decisions.
2. Experience across multiple international markets.
3. Familiarity with data driven decision-making or machine learning concepts, even if they are not the technical users themselves.
4. Cross-industry and cross-regional representation for contextual depth and observing diverse strategic patterns.

After that snow-ball sampling was used to expand on this base of experts. The first participants were asked to suggest others among their networking group who fit the criteria and can offer in-depth insights.

After that, all 9 interviews were transcribed manually and using NVivo software to perform thematic analysis. Following steps were followed:

1. Getting acquainted with the data comprehensively through multiple readings of the transcript and taking notes.
2. Initial Coding with systematic identification of meaningful data.
3. Theme development by grouping the codes
4. Sub-theme development and uncovering hidden patterns and insights
5. Reviewing and Interpreting by synthesizing the final themes into higher order meaning through critical analysis with literature, conceptual and theoretical frameworks, and research objectives

3.4.3 ML Framework Development

Finally, the conceptual framework developed from literature was converted into ML model using KNIME analytics and python. It includes the following steps:

1. Data Import phase using importer node (market size, market potential, external features such as inflation, economic indicators, internal such as financial strength, resources, demographics, country characteristics).
2. Data Preprocessing & Feature Engineering using feature filtering by column filters, statistics, linear regression, correlation filtering, normalizations, categorical encoding.
3. Machine learning models were developed using Random Forests, Decision Trees, SVM, Logistic Regression for supervised, K-means for clustering markets using unsupervised learning mechanisms.
4. Evaluation using Scorers, ROC curves, visualization dashboards, AUC scores.

This framework development’s main purpose is to visualize the conceptual framework into ML models and open a potential for future research to develop the models and apply machine learning into IMS and ES.

3.5 Ethical Considerations

Ethical standards are given top priority throughout the study, with every interview conducted under prior informed consent from the participants, clearly stating the purpose of the research and their rights. Participants were informed that they have the right to withdraw from the research at any point without any adverse impacts. Data confidentiality is always maintained, with every participant’s identity undisclosed to ensure the privacy of the participants. In addition, the sensitive information disclosed during the interviews was given utmost confidentiality and is only shared with authorized parties. The study remains faithful to academic integrity and ethical research practices, being open, fair, as well as respectful to all the participants. Respect for such ethical practice ensures the credibility of the research outcomes and upholds participants' confidence in the research.

CHAPTER 4: ANALYSIS AND RESULTS

The data analysis is divided into three domains which are given below:

4.1 Literature Review Analysis

After a comprehensive analysis of 60 top-reviewed articles, the results are summarized in the following table 4:

Table 4

Literature Review Analysis Summary

Dimension	Sub-Themes	Authors	Key Insights
External Factors	Market Size, Market Potential, Political and Economic indicators, Competition, Cultural Aspects	Root (1998); Islam et al. (2022); Buckley & Casson (1998); Aharoni et al. (2010); Vakratsas et al. (2003); Parry & Bass (1990); Johanson & Vahlne (1977), Maitland & Sammartino (2014)	External Factors guide the IMS & ES such as market size, potential, macro-economic factors but however are misinterpreted by overreliance.
Internal Factors	Tangible Resources (Assets, Finance), Intangible Resources (Experience, Data)	Barney (1991)	Internal factors determine the entry mode and strategy reflecting internal capabilities such as financial strength, resources but limited resources often lead to flawed entry decisions.
Traditional Approach Limitations	Heuristics & Intuition, Follow the Leader Trap, Inadequate	Root (1998); Buckley & Casson (1998); Guercini & Milanesi (2022); Tversky &	Traditional era characterized by lack of data and analytics tools often relied on heuristics, experience, competitor footstep

	Analysis, Managerial Experience and Data Insufficiency	Kahneman (1974); Hilmersson et al. (2022); Fasolo et al. (2024); Vakratsas et al. (2003); Lu (2002); Gentry et al. (2013); Calof & Viviers (2020); Zhou et al. (2012); Cavusgil et al. (2014)	traps, intuition flaws, subjective judgement and cognitive abilities. This led to flawed entry decisions and poor choices of international markets.
Machine Learning Potential	Supervised Learning, Unsupervised Learning, NLP, K-means, Reinforcement Learning	Hsieh et al. (2020); Lewaaelhamd (2023); Alsayat (2022); Rafiei (2024); Sharma et al. (2022); Ezenkwu et al. (2015); Shi (2024); Alantari et al. (2021); Mayer-Schönberger & Cukier (2013); Murphy et al. (2022); Kalra (2023); Sivamayil et al. (2023)	ML has the potential to overcome the traditional challenges by taking a data-driven approach and replace subjective judgement by real time data analysis using supervised models, unsupervised segmentation and clustering, NLP information extractions for data insufficiency and reinforcement learning methods for strategy optimizations but faces limitations in terms of data disparity, biasness, predictive accuracy, and cost implications.

(Source: Created by the Author, 2025)

4.2 Thematic Analysis

After comprehensive literature review, 9 in-depth semi-structured open-ended interviews were conducted to uncover hidden patterns and themes. Majority of our participants were aged between 30 to 60 years with an average age between 35-40 years reflecting their diverse experience in industries such as packaging, agriculture, electronics, FMCG, Rice, Automotive and construction. Industries such as automotive and constructions showed higher potential for ML adoption while other industries ranged from mid to low. Majority of them were reluctant to adopt depending upon their business models, cost implications and current approaches success. Majority of the participants operated in B2C while a few in B2B context. Digital infrastructure was noted majorly low indicating the application of ML taking upto 3-5 years for adoption. All these profile results are summarized in table 5 below:

Table 5

Profile Summary

Interviewee	Role	Industry/Sector	Age	ML Adoption Readiness	Current Tech. Infrastructure
1	Product Manager	Electronics	36	Exploring	Medium
2	Owner	Packaging	44	Low	Low
3	Co-Founder	Agriculture	36	Conceptual	Low
4	Marketing & Export Manager	FMCG	39	Moderate	Medium
5	Export Manager	Rice	34	Low	Low
6	Export Manager	Sourcing	34	Moderate	Medium
7	Export Executive	Automotive	45	Low	Low
8	Director International Sales	Infrastructure	58	High	High
9	Export Director	Construction	50	Very High	Very High

(Source: Generated by NVivo)

4.2.1 Initial Coding

The initial phase of thematic analysis begins reading the transcripts many times and taking nodes. All 9 interviews were transcribed manually, and software aided such as NVivo for the purpose of theme development. Initial codes were generated manually such as "Intuition Based

Decision", "Market Size and Potential", "Gut Feelings", "Managerial Experience", "Potential of Supervised Learning", "Machine Learning Challenges". These codes were verified using NVivo auto-coding feature. Over 300 open codes were generated. A code book was maintained for the record. These 300 open codes were grouped into 5 major clusters: "Traditional Approaches to IMS & ES", "Internal Factors", "External Factors", "ML Potential", and "Challenges to ML Adoption". All these themes with sub themes and their insights are given below:

4.2.2 Themes with Frequency and Interview Quotes

Frequency based analysis was done to illustrate the most prominent themes as discussed by the participants and in relevance with our literature study. This analysis is summarized in table 6 below:

Table 6

Themes Frequency with Quotes

Theme	Sub-Theme	Frequency	Quotes
Traditional Approaches (IMS & ES)	Heuristics, Imitation, Intuition, Experience, Benchmarking, Networking	374	**Int.5:** "When we saw our competitors moving into Middle Eastern Markets, we assumed this market to be profitable and entered." **Int.2:** "Our entry in France was purely based on our founder's experience as he had experience with existing distributors there." **Int.1:** "Our entry into Sri Lanka was disastrous as we

			entered based on our gut feelings and incurred losses up to 70%.” **Int.9:** “When I joined back 10 years ago, there were no digital and analytical tools. Our decisions were limited to boardroom discussions and personal experiences.” **Int.4:** “Our chairman had a gut feeling that our product (spices) worked well in Turkey, and it would work well in Egypt too. We failed to asses’ regulatory indicators and consumer behavior differences.” **Int.7:** “Our Chairman always believed in Market Intuition. ‘This feels right’ and we often incurred costs. “
Internal Capabilities	Tangible resources, Intangible resources	239	**Int.1:** “Even Tho we have financial

			resources but do not have human resources to translate that into tech driven decisions." **Int.9:** "For us, financial resources and data richness are the key resources when we plan to enter new markets." **Int.2:** "We are still using excel and old legacy systems. We are lacking intangible resources in this advanced era, but our business model doesn't require deep analytics."
External Capabilities	Market size, Potential, Macro-economic factors, competition	271	**Int.4:** "GDP, population trends and political indicators are our main triggers." **Int.1:** "Market Size and Ease of doing business are the key for us." **Int.5:** "Political risks halted our move into

			the Afghanistan market.” **Int.3:** “Import regulations matter a lot.” **Int.9:** “Housing trends and construction statistics were used for analysis before we entered Denmark.”
Machine Learning Potential	Supervised Learning, Unsupervised Learning, NLP, Reinforcement Learning	549	**Int.9:** “We are using analytics tools and started using Machine learning for sales planning and forecasting but haven’t applied to IMS and ES.” **Int.4:** “We use machine learning models like Chat GBT for writing purposes only but not for IMS and ES.” **Int.5:** “I believe in the potential of ML for clustering markets and ranking like based on their potentials.”

			Int.2: "We are still using good with our old systems. I don't believe ML will add any value as we are good with our old methods." **Int.7:** "If guided properly I see the potential of ML in customizing strategies based on market differences."
Challenges in Adoption	Business Model, Cost Implications, Company Size, Digital Infrastructure Disparities, Leadership and Cultural Resistance	260	**Int.2:** "We are a small size company and not involved in large dataset analysis. So, I think ML doesn't apply to our business model. **Int.6:** "I feel like ML analyzes large datasets. We have very few B2B customers, and we already have information about them. I believe its true potential in B2C as it doesn't apply to our case. It explores tons of big data." **Int.5:** "We export to Afghanistan where there is digital

infrastructure disparities. There are hardly POS Systems. We find a challenge to apply in our case of exporting to Afghanistan.”

Int.7: “We are still using old legacy offline systems. ML would not add any value as it would be costly to first move to cloud-based system for ML adoption.”

Int.2: “Resistance comes from the top. Leaders prefer human insights with high percentage of non-tech background employees, our mindset and culture resists its adoption.”

(Source: Generated by NVivo)

These results indicate a significant alignment between our participants insights and our study. Traditional approaches to IMS and ES is still dominant with high frequency (374) where majority of our participants have followed traditional methods and some of them are still using them based on their business model. For some, these old approaches were successful while some faced adverse impacts. This remains consistent with our research. Internal factors (239 mentions) and external factors (271 mentions) still aligns with the frameworks of Root (1998) and Barney (1991) as the key inputs to IMS and ES decision-making. However, we got to know some other factors such as Population trends, housing trends, import regulations depending upon the sector and the businesses they operate.

However, Machine Learning Potential (549 mentions) revealed some emerging insights where majority of our participants recognized its conceptual value but stated some challenges with its practical application such as business model variations, cost implications, company size, digital infrastructure disparities, and leadership and cultural resistance. These hidden insights are given below in table 7:

4.2.3 Hidden Patterns with Insights

Table 7

Hidden Patterns with Participant's Insights

Hidden Patterns	Quotes	Insights
Business Model Misalignment	**Int.2:** "ML does not add any value in custom packaging."	Certain B2B contexts are concept driven sales or customized where ML makes no sense.
Cost Implications	**Int.7:** "It would be highly costly first to move to cloud systems and then to ML for IMS and ES." **Int.5:** "Due to our pressing capital needs, ML is a huge investment, and our model is good without it but it will certainly add value in next 5 years."	ML is often deprioritized due to associated investment costs especially in SMEs.
Company Size Limitations	**Int.2:** "We are a small company. This complex data analysis is not our need."	Smaller firms lack intangible resources such as complex data analytical tools. Often,

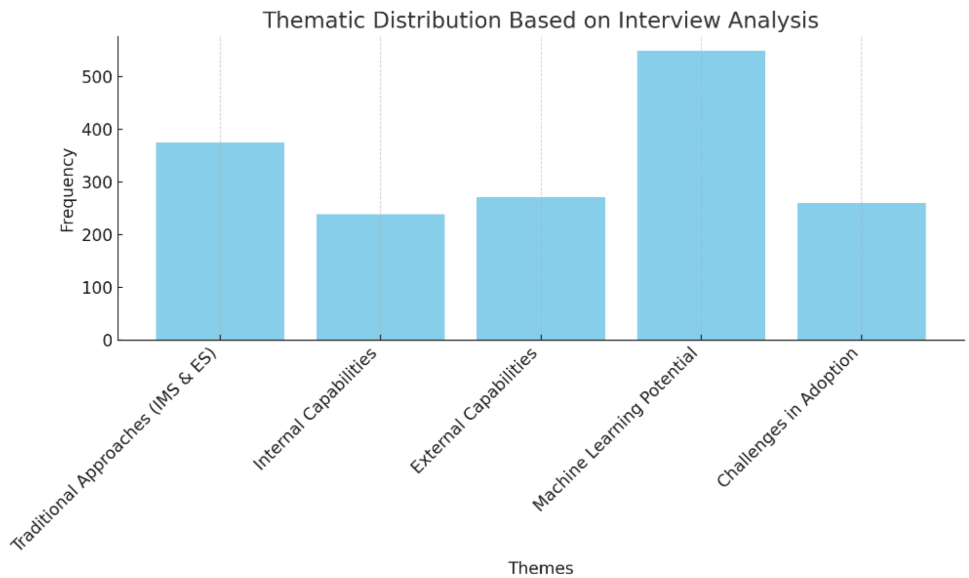
		they don't find a need to analyze big data sets which is the key to ML's success.
Digital Infrastructure Disparities	**Int.5:** "We export to Afghanistan where there is digital infrastructure disparities. There are hardly POS Systems. We find a challenge to apply in our case of exporting to Afghanistan."	Markets are unfit with low digital landscapes making ML adoption a challenge.
Leadership & Cultural Resistance	**Int.2:** "Our board still thinks ML and AI as buzz words." **Int.8:** "If we apply ML to our current processes and fully automate it, there's a chance that machine makes error. Also, our senior seats will become vacant. We fear it."	The fear of getting replaced by machines is acting as barrier to its adoption.

(Source: Created by the Author, 2025)

4.2.4 Thematic Distribution and Insights Analysis

The fig.6 below shows that 32.4% of the mentions were of Machine Learning and its Potential as majority of our participants had the conceptual knowledge but were interested to understand the sequential framework for its incorporation. 22.1% of the mentions discussed the key theme, "Traditional Approaches" where majority of the participants used or are still using traditional methods. Some of them faced negative consequences in their past while some following its success still wants to continue using them. Finally, 16% and 14.1% were the mentions of external and internal resourcing as the inputs to IMS & ES.

Fig.6: Thematic Distribution based on Interview Analysis



(Source: Generated by NVivo)

The participants often relied on heuristics, intuition, benchmarking, follow the leader traps in the past. This wasn't out of ignorance, but it reflected their needs for swift decision-making, previous success with past experiences, and lack of digital tools. One of our participants indicated:

"When we saw our competitors moving into Middle Eastern Markets, we assumed this market to be profitable and entered."

This reflects the follow the leader trap where decision-making relied on external movements and not on in-house analysis. Many firms stated that they deal in certain type of industry where they must follow the leaders. This case highlighted that in fast-moving industries with scarcity of data, imitating the competitor becomes an industry norm.

Many participants are still using conventional intuition framework as their decision-making mechanism. They see intuition not just as a guessing framework but an informed instinct which is shaped by years of diverse experience, multi-national exposures and success factors. For instance, Int.2 reflected that:

"Our entry to France was purely based on their leaders' experience with existing networks and exposure to local culture. Our move was successful so, we followed it over the years."

The tradeoff between "what feels right" Vs. "what data says" has shaped many of the firms' motivation to continue with the conventional methods.

Heuristics play a central role in IMS and ES among our participants. Our participants indicated that they opted these mental shortcuts out of necessity. According to most of the participants, simple rules such as, “Go where the demand is similar”, “Go where you worked before”, and “Replicate the success to similar situation” proved to be successful. Heuristics were chosen as they proved to be beneficial in certain type of industries such as automotive, electronics where delay could turn into missed opportunities. Success of past mostly reinforced their gut instincts. But it was not always true as Int.4 stated:

“Our chairman had a gut feeling that our product (spices) worked well in Turkey, and it would work well in Egypt too. We failed to asses’ regulatory indicators and consumer behavior differences.”

Most of our participants prioritized networking over ML optimized decision making. Several participants relied more on distributor’s feedback, in-person inputs and qualitative research rather than predictive models. They believed that interpersonal approaches are more reliable than the statistical models depending upon the markets, business types and size. Like Int.5 stated that:

“Afghanistan market lacks rich data infrastructure often leading them to trust local contacts more.”

Financial Constraints was another recurring hidden pattern among the participants. This was the case with SMEs and medium sized firms. These firms often perceive ML as a capital-intensive challenge requiring significant funds. As int.7 stated:

“It would be highly costly first to move to cloud systems and then to ML for IMS and ES.” Int.5 stated, “Due to our pressing capital needs, ML is a huge investment, and our model is good without it, but it will certainly add value in next 5 years.”

Their mindsets accept ML as revolutionary tool to the current landscape but not practical due to financial constraints and significant investments. This is because they choose to focus their limited resources towards pressing business needs instead of significantly investing in ML frameworks as they believed their current success does not depend upon ML as doing so would only contribute to additional financial burdens and unnecessary uncertainty.

In addition to the costs, a key hidden pattern emerged was the size of the businesses. As int.2 stated:

"We are a small company. This complex data analysis is not our need."

It suggests that SMEs often see ML frameworks as disproportionate to their needs and company's scale. Our participants indicated that they have few B2B customers with already existing relationships and data. There is no need to do complex ML optimized analysis. This also suggests that ML is the best solution for large sized companies dealing with complex data sets. Like Int.9 stated that they export in more than 26 countries with huge data files.

Business model is the key when choosing the decision framework for IMS & ES. Some of our participants revealed that they operated a small business where they did not find a need to do data-driven decision-making as most of their success came from existing networks and success associated with past experiences. This shows why they often relied on traditional approaches depending upon their business model and needs. For instance, as per Int.2:

"ML doesn't add any value in packaging business as they deal with a few B2B customers and have data on them. There is no need to do analysis on existing partners."

Another critical bottleneck was the human resource. Our participants indicated that digital transformation utilizing ML is more about people than costs. This is because many firms have a large proportion of employees that are not tech-savvy. The resistance to change can have adverse impacts on the business model. Another reason why they chose traditional approaches was familiarity bias and cognitive ease. Int. 4 found Egyptian market to be like their home. Lastly, int.7 stated that they believed in market intuition because of their culture legacy and leadership. A lot of company's leaders are doing the same thing trusting their experience over data for years and continue doing this even if they face negative consequences. This reflects overconfidence.

Cognitive inertia, driven by resistance to change was found to be another factor motivating participants to opt. conventional methods. This case was evident mostly in family-owned businesses. Int.2 and Int.9 stated that the use of old legacy systems, established business models and leadership habits restricted digital transformation. As one of the participants stated:

"Resistance comes from the top. Leaders prefer human insights with high percentage of non-tech background employees, our mindset and culture resists its adoption."

Many of the participants resisted because of the fear of getting replaced by machines. They believe ML will take their place and were reluctant to introduce ML to IMS & ES as one of our participants stated:

"If we apply ML to our current processes and fully automate it, there's a chance that machine makes error. Also, our senior seats will become vacant. We fear it."

So, the organizational mindset plays a key role in progressing from the traditional approaches to ML optimized decision-making. Many leaders resist this change because of having high percentage of non-tech savvy workforce. They fear massive structural and business model changes. Employees should be educated on the potential benefits of ML as a tool for complementing their intelligence not as their replacement. It has the potential to bring efficiency to the current practices.

Limited exposure to data-driven tools also plays a key role in restricting digital transformation. As one of our participants stated:

"When I joined back 10 years ago, there were no digital and analytical tools. Our decisions were limited to boardroom discussions and personal experiences."

Int.4 stated that they use AI and ML just for writing purposes. Training workforce, radical business model changes, time, costs, and uncertainty are the key barriers. This factor leads majority of our participants to continue with the conventional methods. Lack of access to local market data often led the leaders to rely on traditional approaches. Like int.5 stated that in regions like Afghanistan with data scarcity, they fell into the trap of word of mouth and competition. So, intuition and heuristics became their substitutes for research and analysis.

All these insights show that they were chosen out of necessity by our participants and not blindly chosen. They were shaped by practical experiences, past success stories and business models. Almost, all the participants acknowledged the value of ML in IMS & ES but few of the participants showed interest in its practical application. Many big firms operating in sectors like IT and construction showed the most interest in adopting ML in areas such as country segmentation, classification and optimizing ES strategies utilizing RL.
As int. 9 stated:

"We are using analytics tools and started using Machine learning for sales planning and forecasting but haven't applied to IMS and ES. We are in planning phase. Our IT and Finance teams are already in planning phase for its practical implementation."

Similarly, Int.7 stated:

"If guided properly I see the potential of ML in customizing strategies based on market

differences."

Int.5 stated:

"I believe in the potential of ML for clustering markets and ranking like based on their potentials."

Most of our participants were purposely chosen from the top levels to understand how they perceive the potential of ML in IMS & ES. Majority of them were highly specialized in IMS & ES but had little knowledge about ML. They were properly explained the framework of ML. While some of the participants had knowledge of ML. These results suggest that while the path to ML adoption in IMS & ES is characterized by firm-specific realities, the growing acknowledgment of its value requires an incremental, tailored-transformation. Ultimately, ML is not a replacement for human intelligence but a tool that amplifies it through accuracy and precision.

4.2.5 Thematic Interrelation Matrix

To further enrich thematic analysis, we performed thematic interrelation analysis. Each theme was evaluated against others based on qualitative aspects, NVivo co-coding, manual insights and frequencies to understand the correlation among themes. A scoring was used with 0 as no overlap, 1 as weak interrelation, 2 as moderate and 3 as strong. This was done to understand the extent to which one theme influenced the other theme and to find overlaps between them. This matrix is given in table 8:

Table 8

Thematic Interrelation Matrix

	Traditional Approaches	Internal Factors	External Factors	Machine Learning Potential	Challenges
Traditional Approaches	3	2	2	1	3
Internal Factors	2	3	2	2	3
External Factors	2	2	3	2	2
Machine Learning Potential	1	2	2	3	3
Challenges	3	3	2	3	3

(Source: Generated by NVivo)

- **Traditional Approaches ←→ Challenges (Score 3):** Participants who relied on heuristics-based decision making in IMS & ES (Int.2, 5, 7) often emphasized resistance towards machine learning adoption based on their business models, current infrastructure and legacy systems, and resistance to change. This was because they came from family-owned businesses and SMEs. Many factors such as old legacy systems, cultural comfort with past experiences and success factors, limited budget and technological resistance were the key reasons of their resistance. They believed that ML would lead to radical changes to their business models, unnecessary additions to financial budget and significant training for their workforce. This would change the entire landscape of their current business in terms of strategy, workforce, costs, technology, vision and mission.

- **Internal Factors ←→ ML Potential (Score 2):** Participants emphasized that key internal factors such as digital tools, data skills, infrastructure are the key enablers of ML in IMS & ES. (Int.1, 6, 9) This is because our participants believed that ML optimized decision-making frameworks are not just plug-and-play but require significant changes to internal resources. This was the case with majority of the SMEs but not with large size firms such as Int.9. Large firms showed more interest in the potential of ML due to rich internal resources ready to accept and implement ML optimized frameworks.

- **External Factors ←→ ML Potential (Score 2):** Participants indicated several factors such as GDP, inflation rates, population trends, and political indicators as key inputs to ML models. (Int.3,9) They see these factors as the top inputs for predictions and modelling decisions. They play a key role in demand forecasting, country ranking, insights predictions and segmentation.

- **Challenges ←→ Internal Factors (Score 3):** Participants (Int.1, 2, 5) stated lack of CRM, analytical tools, tech staff and cloud-based systems acted as barriers to ML adoption. They see those challenges not only in terms of costs but overall transformation. As, shifting towards ML optimized decision-making framework require a radical change in workforce education, technology investment, cloud-based integration, replacement of old legacy systems, and internal mindset changes.

- **ML Potential ←→ Challenges (Score 3):** Almost all the participants showed interest in ML potential but were immediately undercut by business model variations, resistance to change, cost implications, and other factors. This was because they feared reality checks. Fear of getting replaced by machines was the most significant as most of our participants were highly experienced in conventional way.

4.3 ML Framework Development

Based on the conceptual framework outlined in Fig.4 and informed by insights from literature, KNIME Analytics platform was used to visually create a sequential ML framework for its adoption to IMS & ES as given below in four phases:

4.3.1 Data Import & Preliminary Analysis Phase

The first phase dealt with using nodes such as data import, statistics, value counter, correlation, bi-variate analysis, numeric outliers and group by nodes in KNIME analytics. The data can be extracted using NLP and can include features such as financial resources, tangible and intangible resources, GDP, demographics, Inflation rates, Market Size, Market Potential, Competitors, Macro-economic indicators, countries list and other depending upon business type and sector. The nodes such as statistics, numeric outliers, correlation will help in identifying the key statistics about the market size, population, trends and potential. Correlation nodes will help in finding the correlations between markets and other features as per the requirements. This is shown below in fig.7:

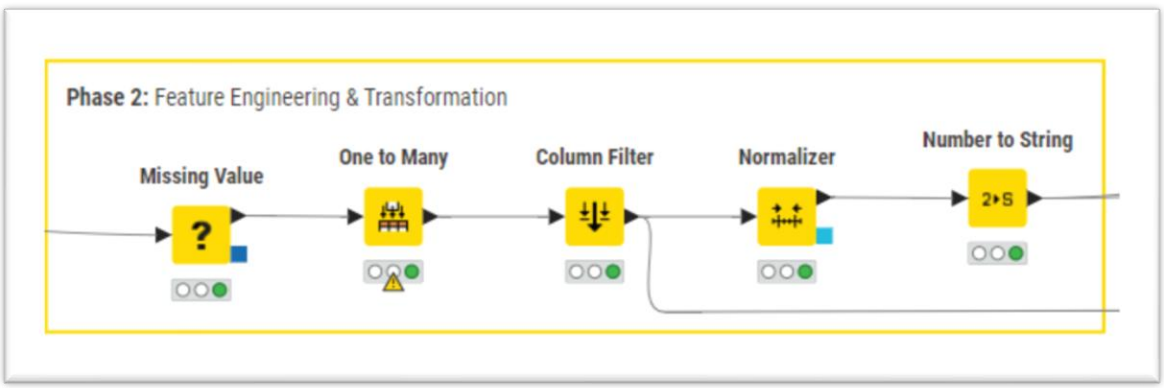
Fig.7: Data Import and Preliminary Analysis

(Source: Created with KNIME Analytics)

4.3.2 Data Preprocessing and Transformation Phase

The next phase dealt with cleaning of features and feature engineering using nodes such as column filters to remove unnecessary features such as country code, Product codes, etc; missing value nodes for overcoming data disparity issues, one to many node for coding categorical features such as gender, education of the consumers; normalizer for coding the data in 0,1s format in order to be readable by machine and remove any model bias. The whole process is done to make ML models more and more efficient for making IMS & ES decisions. This is shown in fig.8 below:

Fig.8: Feature Engineering and Transformation



(Source: Created with KNIME Analytics)

4.3.3 Machine Learning Models (Supervised, Unsupervised)

The next stage dealt with visualizing ML models for making decisions related to IMS & ES. Three models were chosen: Logistic due to its simplicity, Random Forest as an ensemble of decision trees for its capacity and SVM (Support Vector Machines) for understanding non-linear relationships. Cross-Validation was used using X-partition with 10 folds for reducing bias and increasing accuracy. Various additional nodes were used such as SMOTE for data balancing, Gradient boosters for improved performance. This is where our data for IMS & ES will be fed, and the results will be predicted. Learner node will learn from the international market data and predictor will make decisions. Finally, K-means can be used to cluster markets based on similarities. All these models are shown in Fig.9-12 below:

Fig.9: Logistic Regression

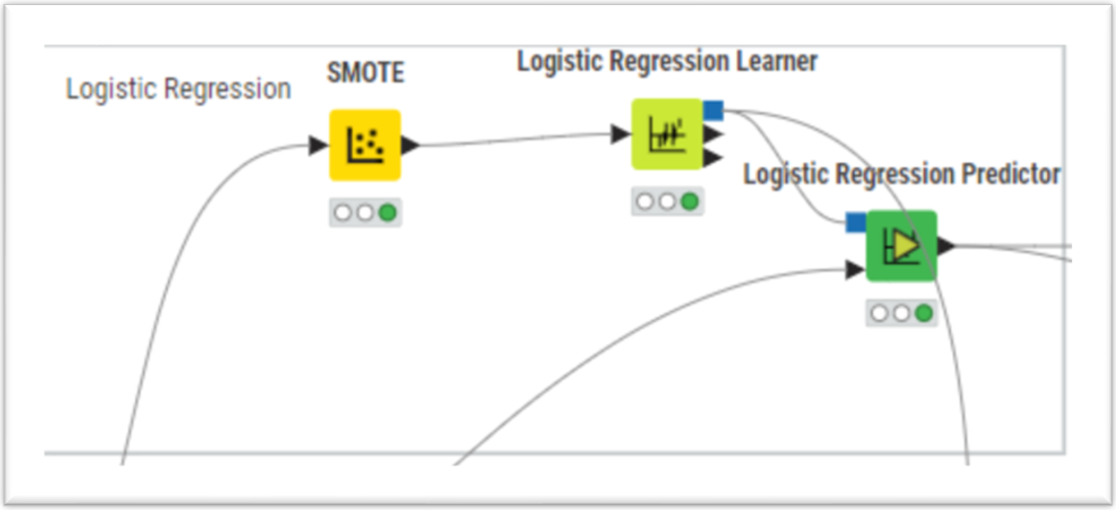


Fig.10: Random Forest

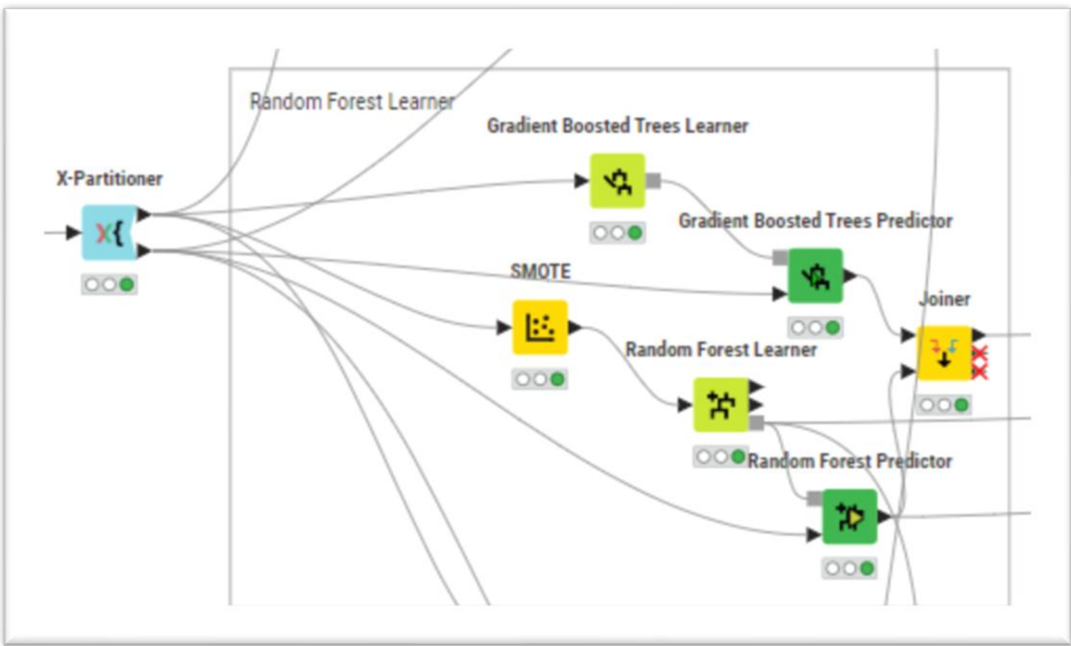


Fig.11: Support Vector Machines

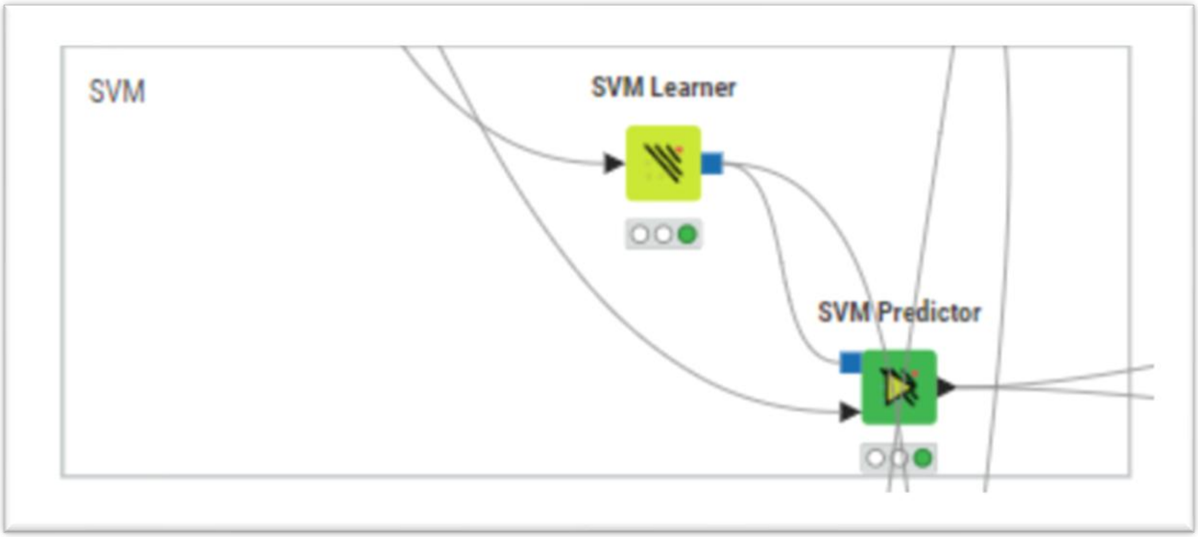
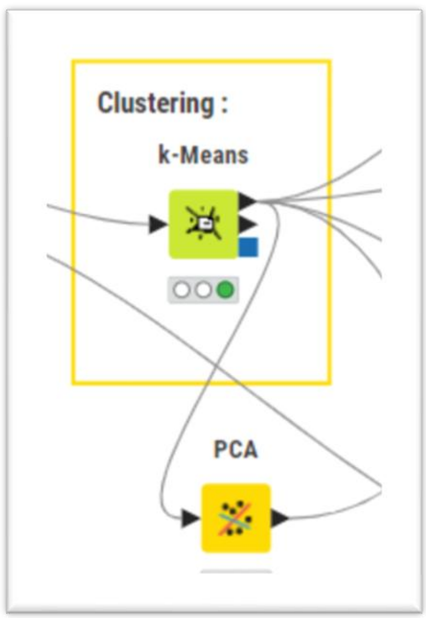


Fig.12: K-Means Clustering



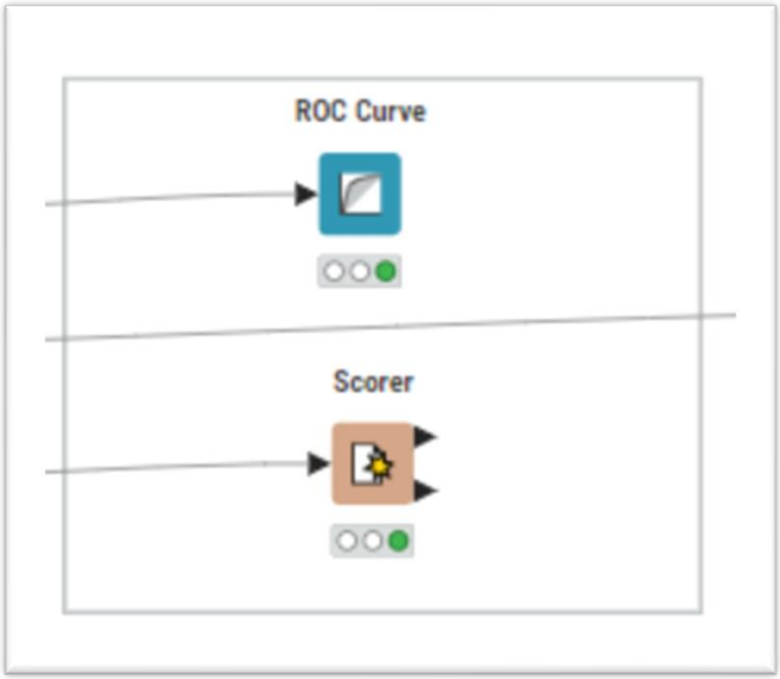
(Source Fig.9-12: Created with KNIME Analytics)

4.3.4 Evaluation Phase

The final and most important phase in our framework is evaluation phase which will give the results on the accuracy of our model in terms of recall, sensitivity, precision, predictability, ROC curve, AUC scores for finding the accuracy in terms of true positives. This is shown in fig.13

below. After evaluating, changes can be made to make the model better or by reflecting human insights and consultation. Finally, this framework can be developed to build ML models which can make predictions on market selection and entry.

Fig.13: Evaluation Phase



(Source: Created with KNIME Analytics)

4.4 Findings and Results

The findings of this study provide a compelling narrative on how firms approach IMS and entry in the context of machine learning and its potential. As per Root (1998) and Barney (1991), internal indicators such as tangible and intangible resources; external indicators such as the size of market, potential, competition, and macro-economic factors shape these decisions. Despite advancements in digital technologies in the era of digitalization, many firms still rely on traditional approaches such as heuristics, intuition, gut feelings, managerial experience, follow the leader trap and inadequate analysis for entering international markets. This aligns with the framework by Root (1998) where these traditional methods often led to negative consequences. However, research shed light on the potential of ML in revolutionizing the traditional landscape of IMS & ES. Technologies such as supervised and unsupervised learning has the potential to overcome challenges associated with heuristics, intuition, gut feelings, imitation and managerial experience. Whereas, NLP has the potential overcome challenges such as data insufficiency and inadequate analysis by offering accurate, precise data-driven decision making. However, there are some challenges associated with its adoption such as data quality issues, cost, infrastructure disparities and prediction uncertainties.

Our results indicate a significant alignment between our participants insights and our study. Participants were selected using purposive and snow-ball sampling methods. Their profiles reflected diverse experience, sectors and top-level positions in International Market roles. Majority of our participants indicated their reliance on traditional frameworks for IMS & ES. Some participants faced negative consequences in past as Int. 1 faced losses up to 70% while entering Sri-Lankan market based on gut feelings, Int. 5 simply followed the footsteps of their competitors in Middle Eastern market, Int. 4 entered Egypt following the success in Turkish market based on experience and inadequate analysis only to find a set-back due to regulatory and consumer behavior differences, Int.7 stated that their chairman relied on market intuition as it felt right. However, in some cases, losses were incurred due to inadequate analysis on international markets. Whereas, in some cases, they had success. For instance, participants in fast moving industries relied on leader's footsteps and competitor's imitation to match the pace and stay competitive. Few participants see intuition not just as a guessing framework but an informed instinct which is shaped by years of diverse experience, multi-national exposures and success factors. Some of the participants relied on business networks as a more reliable way of dealing business in-person especially in emerging economies such as Afghanistan where the scope of digitalization is limited. Majority of our participants had a conceptual knowledge about ML and it's potential. However, only Int. 7 and Int. 9 expressed optimism towards its practical application while the other participants were skeptical. This is highlighted in the thematic interrelation matrix where ML Potential ←→ Challenges (Score 3) revealed that the participants were reluctant due to business model variations, old legacy systems, cost implications and other factors. Participants (Int.1, 2, 5) stated lack of CRM, analytical tools, tech staff and cloud-based systems acted as barriers to ML adoption.

To address these barriers and provide a sequential framework to follow, this research developed a 4-phase comprehensive ML framework to guide future researchers, managers and data scientists. KNIME analytics platform was used to visualize the framework. The first phase included data set analysis by NLP extractions and data import. Comprehensive tools such as correlation filters, bi-variate analysis, descriptives has the potential to overcome the inadequate analysis and data insufficiency challenges. The second phase dealt with feature engineering and transformation to remove any bias from the data and improve predictive capabilities. Thirdly, supervised ML models such as Support Vector Machines, Logistic Based Model, Random Forest Model were used optimized with the best hyperparameters and cross-validation to improve predictive accuracy. K-means (unsupervised learning) was used to segment markets based on similar characteristics. This phase will make accurate data-driven decisions on IMS & ES without the reliance on heuristics, intuitions, gut feelings, managerial experience and imitation. Finally, evaluation phase dealt with key performance indicators for our models in terms recall, sensitivity, precision, accuracy, ROC, and AUC scores to make model efficient and precise. However, insufficient data and time constraints associated with complex data collection, only the framework was visualized setting the directions for future researchers to build ML models. These models can be applied after development to test data to make predictions on countries selection, ranking these countries, grouping them by similar characteristics and improve strategies based on active feedback system utilizing reinforcement learning. However, it acknowledges that Machine Learning is not a plug and play solution to traditional methods but a comprehensive tool that must align with firm overall capabilities and infrastructure, culture and business model.

Moreover, our research uncovered some hidden insights based on in-depth open-ended interviews. Factors such as business model variations, cost implications, digital infrastructure disparities, company size and resistance often undercut our participant's responses towards its adoption. Cost implications was observed mostly in the case of SMEs where ML investments were deprioritized. Smaller firms lack intangible resources such as complex data analytical tools. Often, they don't find a need to analyze big data sets which is the key to ML's success. Many participants were happy with their current business model success and were not open to change. This case was highlighted in Int.2 indicating certain B2B contexts are concept driven sales or customized where ML makes no sense. Moreover, Smaller firms often lack intangible resources such as complex data analytical tools. Often, they don't find a need to analyze big data sets which is the key to ML's success. Another case highlighted in Int.5 discussed the potential failure of ML adoption in countries like Afghanistan due to digital infrastructure disparities. Markets are deemed unfit with low digital landscapes making ML adoption a challenge. Lastly, we observed resistance to change in some of our participants. As int. 8 stated, "Our senior seats will become vacant if we fully automate IMS & ES process with ML". Some of the participants were in the favor of hybrid model characterized by both machine learning and human insights. However, the fear of getting replaced by machines is acting as barrier to its adoption.

Almost all the participants acknowledged the potential of ML in revolutionizing the IMS & ES framework. The hesitance in its adoption should overcome through workforce education of ML as tool complementing their intelligence not as a replacement. Many big firms operating in sectors like IT and construction showed the most interest in adopting ML in areas such as country segmentation, classification and optimizing ES strategies utilizing RL. These results suggest that while the path to ML adoption in IMS & ES is characterized by firm-specific realities, the growing acknowledgment of its value requires an incremental, tailored-transformation. Ultimately, ML is not a replacement for human intelligence but a tool that amplifies it through accuracy and precision.

CHAPTER 5: CONCLUSION

This research aims to critically examine the potential of ML in addressing the inherent limitations of traditional methods to IMS and ES, an area that has been historically dominated by gut feelings, experiential reliance, intuition, heuristics, competitor imitation and inadequate analysis. By comparing and contrasting, the traditional decision-making framework outlined by Root (1998), Buckley & Casson (1998) and Barney (1991) with the new possibilities enabled by ML, this research fills a significant gap in both managerial practice and existing literature.

More than 75 scholarly articles were thoroughly reviewed from top journals. The existing literature established that traditionally International Market Selection (IMS) and Entry Strategies (ES) decisions were shaped by internal factors including tangible and intangible resources and factors such as the size of market, potential, competition, macro-economic factors and demographics. However, these frameworks were often unconventional, relying on heuristics, intuition, gut feelings, competitor imitation and managerial experience. Works by Maitland & Sammartino (2014) and Ahi et al. (2016) criticized these approaches as impulsive, overly simplistic, and inappropriate for today's complex and hypercompetitive landscape. This research confirmed these critiques through in-depth open-ended expert interviews, where top level decision-makers in IMS & ES acknowledged cases of market failure due to heuristics, intuition, gut feelings, follow the leader trap, or inadequate analysis.

At the same time, the existing research strongly emphasizes the cathartic potential of digital tools particularly machine learning (ML) in the era of digitalization to enable data-driven strategic decision-making. Various ML techniques such as supervised learning has the potential to overcome challenges associated with heuristics, intuition and gut feelings by informing data-driven decision-making; unsupervised learning can help in clustering international markets based on real-time data; NLP extracting meaningful insights can overcome problems associated with data insufficiency and reinforcement learning can improve strategies through trial-and-error learning approach. Yet the integration of ML in IMS and ES remain under researched, which this study aims to address.

To ensure a strong methodological approach, this study adopted a triangulated three-tier validation strategy:

- Literature Review Analysis from top reviewed journals critically analyzing 75 papers.
- Thematic Analysis with sub-themes, quotes, frequency counts, distribution and thematic interrelation matrix based on 9 expert interviews.
- Comprehensive Framework development to visualize sequential ML approach in IMS & ES using KNIME Analytics.

Majority of our participants indicated their reliance on traditional frameworks for IMS & ES indicating a significant alignment with our research. Their insights also revealed some real cases where traditional approaches guided by intuition, gut feelings, experience and imitation led to adverse impacts. The study established that while Machine Learning’s potential is widely recognized, its adoption in IMS & ES remains limited. This reluctance from our participants was due to business model variations, old legacy systems, cost implications and other factors. Lack of CRM, analytical tools, tech staff and cloud-based systems also acted as barriers to ML adoption. To bridge this gap, a comprehensive visual framework was developed using KNIME analytics platform covering data collection, market predictions, clustering and segmentation, country ranking, forecasting and dashboard support systems. It provides a roadmap for progressing from traditional approaches to ML optimized efficient and accurate decision-making. Moreover, this study uncovered some hidden patterns such as business model variations, company size, data infrastructure disparities, cost implication, cultural and leadership resistance due to fear of being replaced by machines. These patterns form the basis for future research on the success factors and failures of ML in IMS & ES.

In conclusion, this research assert that Machine Learning (ML) holds a significant potential to reshape International Market Selection (IMS) and Entry Strategies (ES), but this transformation depends on firm readiness, innovative mindset, and data enriched environment. Machine Learning (ML) is not a replacement for humans but most effectual when integrated with human insights into a hybrid framework for decision-making.

5.1 Limitations of the Study

While this research provides valuable insights into IMS & ES through a machine learning approach, there are some limitations that must be acknowledged. Firstly, the sample size was 9 with top level decision-makers from diverse industries due to time constraints. However, these results cannot be generalized to whole population. Secondly, there was overrepresentation of SMEs and B2B firms in our sample. Larger firms could have uncovered different patterns on ML adoption. Thirdly, this research follows purely a qualitative research design based on existing literature and expert interviews. So, the subjectivity of interpretation is largely influenced by researcher's lens. Lastly, a comprehensive framework was developed using KNIME analytics. However, due to limited time and complex data collection constraints, the framework could not be developed into a real model testing actual market data. As a result, this framework remains conceptual.

5.2 Value of the Study

While ML brings efficiency and improvements to IMS & ES, this research provides significant value for leaders and managers to educate their workforce on the importance of ML as a hybrid tool in overcoming the inherent challenges associated with conventional approaches complemented by human insights, a practical framework for implementing ML in their IMS & ES decision-making framework, identifying the need for ML adoption by analyzing their size, sector, business model and culture, and overcoming the barriers posed by heuristics, inadequate analysis, data insufficiency and subjective judgements. This study not only sheds light on the potential of ML, but realistic understanding of challenges associated with its practical implementation for leaders and managers in terms of cost, digital infrastructure disparities, cultural and leadership resistance.

5.3 Directions for Future Research

This study opens the directions for future researchers in the following ways:

- Testing of Framework with actual market data with real-world scenarios through empirical testing.
- Increasing the sample size with larger firms to uncover different patterns to ML adoption and hybrid participants with domain expertise in both ML and IMS.
- Grasping how leaders and organizational culture influence the adoption of ML.
- Finding the key success factors and failures associated with ML in IMS & ES.
- Longitudinal case studies to measure outcomes of the firms implementing ML in IMS & ES.

In conclusion, this research acts as the guiding map for the managers planning to implement ML in International Market Selection (IMS) and Entry Strategies (ES). Future researchers can build upon this groundwork to expand the horizons of IMS and ES in this era of digitalization.

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APPENDIX

Interview Questions:

Section A: Introduction

- Can you briefly describe your role in international market entry decisions?
- How do you generally feel about the application of AI or machine learning to strategic decision-making?
- Has your business or you tried using machine learning in any aspect of strategic planning?

Section B: External Factors (Root's Model – 1998)

- What external market conditions do you typically evaluate when assessing a new country?
- How do you assess factors like market size, competition, or growth potential?
- How do risks related to politics, the economy, or culture affect your choices?
- Have you experienced situations where external conditions clashed with intuition or internal priorities?
- Can you describe a time when external factors produced an unexpected or counterintuitive result?

Section C: Internal Factors (Resource-Based View – Barney, 1991)

- What internal capabilities (e.g., strategic expertise, financial strength, data infrastructure) shape your decisions?
- How do you make use of internal knowledge, past experience, or in-house analytics?
- Are there internal gaps (technical, knowledge, people) that limit your market expansion confidence?
- How do you balance the attractiveness of the external market with internal capabilities?
- Do you believe your firm is technologically equipped to analyze complex markets?

Section D: Traditional Approaches & Limitations

- How have you traditionally approached international market selection and entry?
- What tools or frameworks have you used (e.g., heuristics, past success, intuition, follow

the leader, benchmarking) and why?

- What are the strengths and weaknesses of these traditional methods in your view?
- Can you recall a time when experience or intuition led to flawed assumptions?
- Are there certain international contexts where conventional approaches seem less effective?

Section E: Machine Learning — Strategic Fit & Value-Add

- Have you ever used or considered machine learning in strategic decision-making?
- Where do you see potential for ML to add value and improve the international market entry process?
- Could ML tools and models (supervised, unsupervised, reinforcement learning) support how you evaluate:
    - External market risks?
    - Internal readiness or capability alignment?

  and why?
- What decision points (e.g. market prioritization, scenario planning) might benefit from ML?
- Why might ML be helpful and why might it not succeed in gaining traction in your environment?
- What specific tasks or decision points could machine learning realistically support?

Section F: Human Judgment, Culture & Organizational Readiness

- What are the primary leadership, technical, or cultural obstacles to ML adoption?
- How do you compare human intuition to data-driven insights in high-stakes decisions?
- Do you think machine learning will be used as a support tool or as something more independent in the future?
- What organizational changes (skills, mindset, leadership) would be required to fully integrate ML into strategic decisions?