E-ISSN: 3063-0304, P-ISSN: 3063-1092
Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 3, December 2024, Page 140-252
https://doi.org/10.69725/raida.v1i3.170

Contents lists available at Inovasi Analisis Data

Researcher Academy Innovation Data Analysis

journal homepage: https://analysisdata.co.id

Enhancing Operational Performance: The Role of Entrepreneurial Orientation, Big Data Analytics, and AI Under Environmental Dynamis

Srinivants Cherla [a], **Prajda Sharma** [b]

[a] *Department of Science and Technology, Ministry of Science and Technology, Govt. of India, Technology Bhavan, New Delhi, India*
[b] *Department of Science and Technology, Ministry of Science and Technology, Govt. of India, Technology Bhavan, New Delhi, India*

ARTICLE INFO

Article history:
Received 7 April 2024
Revised 6 june 2024
Accepted 10 September 2024

Author's correspondence;
Srinivats

Keywords:
Nonparametric tests, computational intelligence, data mining, post hoc analysis, statistical reliability

ABSTRACT

Objective: This study investigates the relationships between Entrepreneurial Orientation (EO), BDA-AI adoption, Operational Performance (OP), and the moderating role of Environmental Dynamics (ED). The study aims at exploring the impact of strategic orientation and advanced technologies on organizational capabilities in the uncertain contexts.
Methods: We employed a quantitative analysis using Structural Equation Modeling (SEM) with Warp PLS to test the hypothesized relationships. The measurement model was then checked for reliability and validity and fit indices were calculated to ascertain robustness. Because this was a multi-year initiative, data were collected over time and included a number of metrics associated with operational improvement and technology adoption.
Results: The result showed a significant and positive association of EO, BDA-AI adoption, and OP. These relationships were greatly strengthened by ED, highlighting ED as an engine of organizational adaptability and performance in both dynamic contexts and organizations. The proposed structural model was able to explain quite a lot of the variance in the data and fit her extremely well according to the model fit indices.
Novelty: Therefore, this study proposed ED as a crucial mediating variable to help unite the excess between the strategic education and innovative performance. It offers a unique lens through which to view the ways in which firms use EO and advanced analytics to maintain competitive advantage under conditions of environmental turbulence.
Implications for Research: The study provides a conceptual basis for future empirical research on the strategic coupling of EO and BDA-AI in sectors. It opens up avenues for consideration of environmental and organizational influences that enable or inhibit the performance-induced benefits of technology innovations

1. Introduction

The pace of transformation in BDAs and AIs have provided advanced means to control the manufacturing process and improve the organization overall efficiency (Arvidsson & Dumay, 2022; Naseer et al., 2023; Saggi & Jain, 2018). It allows firms to handle huge quantities of data, streamline supply chains, and create out-of-the-box solutions to keep pace with rapidly changing market requirements (Haleem et al., 2022; Patel et al., 2022; Troisi et al., 2020). Since the global markets as well as the consumer preferences are getting much more complex, BDA along with AI have become a necessity for firms to improve the operational performance as well as competitive advantage (Benzidia et al., 2021; Dubey et al., 2020). Recent research papers have highlighted the especially transformative capacity of these technologies as they can significantly drive down costs and enable products to be delivered much quicker while providing support for evolving capabilities (Ghosh et al., 2022; Warner & Wäger, 2019). What remains is the business problem of managing technology and aligning organizational strategies with the adoption of these technologies in turbulent and unpredictable environments (Durst et al., 2024; A. Kumar & Shankar, 2024; Tallon et al., 2019).

Operational agility is vital in there, manufacturing organizations have to learn continuously in this volatile, uncertain, complex and ambiguous (VUCA) world. Specifically, although entrepreneurship orientation (EO) has been recognized as an influencer of innovative practices, its function in fostering the adoption of BDA-AI and its effect on operational performance have remained uncertain (Shafique et al., 2024; Tan et al., 2024; Zhang et

E-ISSN: 3063-0304, P-ISSN: 3063-1092
Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 3, December 2024, Page 140-252
https://doi.org/10.69725/raida.v1i3.170

al., 2022). These challenges are heightened within contexts characterized by environmental dynamism, where rapid shifts in the market, changing customer needs, and new technologies contribute to environmental uncertainty and complicate decision-making (Haarhaus & Liening, 2020; S. Kumar & Bhatia, 2021; Wamba et al., 2020). In addition, skepticism regarding the genuine advantages of BDA-AI adoption continues, as organizations tend to mention hindrances including inadequate resources, insufficient technological infrastructure, and unwillingness to adapt (Costa et al., 2023; Luqman et al., 2024). These challenges highlight the need for greater understanding of the ways in which EO, BDA-AI and environmental dynamism interact with one another to impact operational outcomes.

This study rests on two complementary theoretical lenses: dynamic capabilities view (DCV) and contingency theory (CT). The Dynamic Capability View (DCV) argues that firms with strong dynamic capabilities can respond to changes in the environment and earn sustainable competitive advantage (Ferreira et al., 2020; Mathivathanan et al., 2017). It highlights the need to sense opportunities, seize them, and reconfigure organizational resources according to changing market conditions. In contrast, CT argues that the effectiveness of organizational strategies depends on some contextual factors such as environmental uncertainty and dynamism (Bavaresco et al., 2023; Ferreira et al., 2020). Such initiatives are crucial, and recent literature demonstrates the need to integrate the theoretical perspectives, given how EO can fuel the adoption of innovative technologies that enhance operational performance (Ameer & Khan, 2023; Chowdhury et al., 2023; Shahzad et al., 2020). This study aims to address some gaps regarding how EO and BDA-AI contribute to organizational success in dynamic environments through the lenses of DCV and CT.

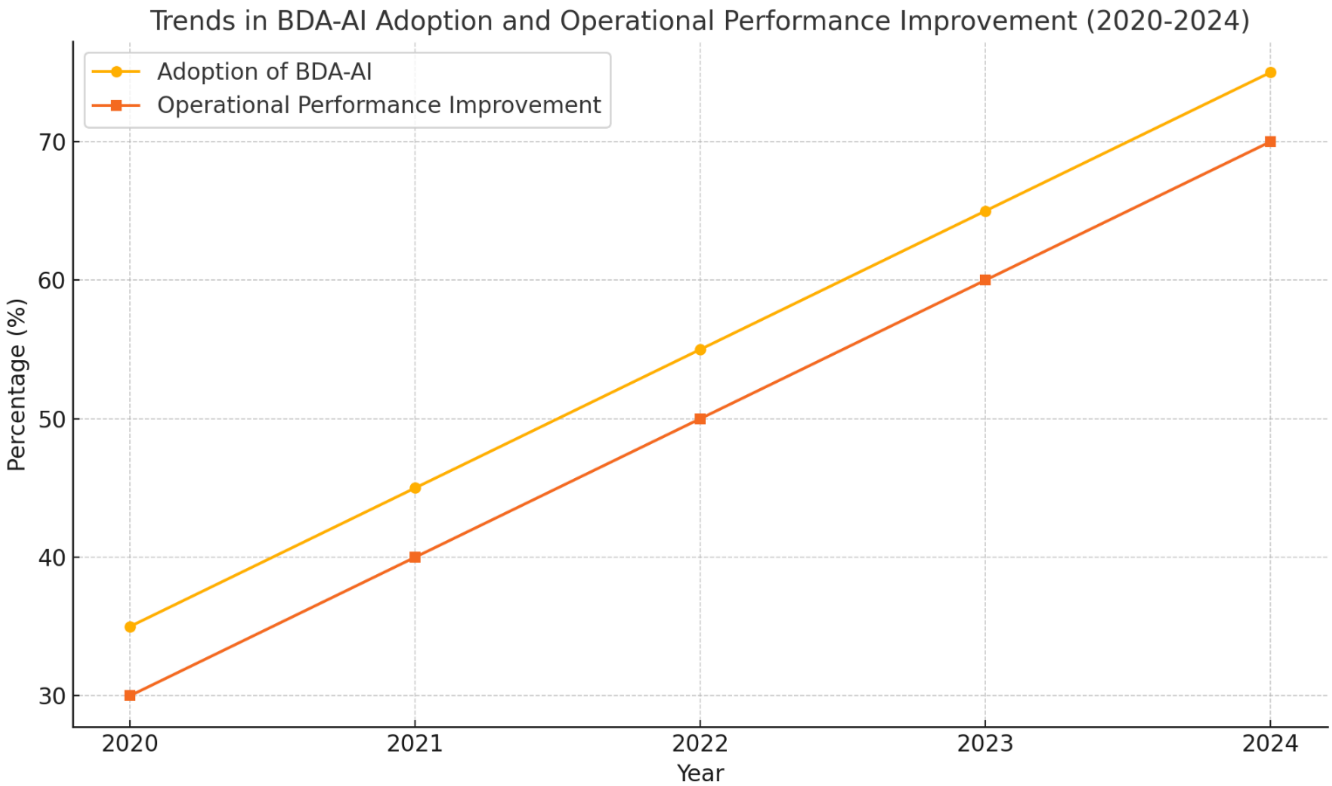

Figure 1. Fenomena trends in BDA-AI adoption and operational performance improvement from 2020 to 2024

Even though the literature is gradually recognizing the significance of emerging technologies in operations management, the relationship of the triad EO, BDA-AI and the environmental dynamism is being rooted out scantily. Prior research has mostly focused on direct relationships between BDA-AI and operational performance Benzidia et al. (2021), Dubey et al. (2020), while the moderating effects of environmental dimensions attributes have

E-ISSN: 3063-0304, P-ISSN: 3063-1092
Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 3, December 2024, Page 140-252
https://doi.org/10.69725/raida.v1i3.170

received limited attention. For instance, though EO has been shown in some studies to be positively related to technology adoption Andati et al. (2022), Hanham et al. (2021), it has demonstrated inconsistent or negative associations, especially in highly dynamic environments in others (Sun et al., 2017; Wang et al., 2021)). These differences illustrate the necessity of exposing the contextual circumstances that determine the efficacy of EO and BDA-AI. Furthermore, there is limited empirical evidence of how organizations utilize EO to cope with environmental dynamism and achieve better performance (Dubey et al., 2020; Ferreira et al., 2020). Our work thus adds to the literature by developing a new framework that merges EO, BDA-AI and environmental dynamism, showing their potential operational performance effects.

The objective of this study is to find the interaction effects between the constructs of entrepreneurial orientation, artificial intelligence-based big data analytics, and operational performance in different levels of environmental dynamism. It aims to determine the avenues through which EO enhances adoption of BDA-AI, analyze how environmental factors moderate this relationship, and offer actionable insights for manufacturing firms functioning in dynamic and uncertain ecosystems. In meeting these objectives, the research not only contributes to theoretical advancement but also provides practical recommendations for harnessing technological advancement within the manufacturing industry.

2. Theoretical framework and development

2.1 Theoretical research

This study has a theoretical basis on Dynamic Capabilities View (DCV) and the Contingency Theory (CT) which help understand how organisations can adapt to transforming contexts by using their internal capabilities. DCV stresses an organisation's capability to combine, develop and recreate internal and external competencies to respond to quickly and unreliably changing surroundings (Teece et al., 1997). That is an important way to see to what extent entrepreneurial orientation (EO) results in innovation as well as the acceptance of cutting-edge technologies such as Big Data Analytics and Artificial Intelligence (BDA-AI). Building on this, contingency theory posits that organisational performance is contingent on fit with external environmental factors (Lawrence & Lorsch, 1967). Recent studies emphasize that by synergizing entrepreneurial capabilities with new-age technologies like AI, firms can proactively respond to market volatilities (Eisenhardt & Martin, 2000; Chen et al., 2020). Additionally, there is a significant impact of the interaction of the technology adoption and environmental conditions on operational effects (Donaldson, 2020). By integrating these theories, the study seeks to present clear relationships between EO, BDA-AI and operational performance (OP) and identifies environmental dynamism as a moderator.

2.2 Entrepreneurial Orientation (EO) and Adoption of Big Data/Artificial Intelligence (BDA-AI)/Operational Performance (OP)

Entrepreneurial Orientation (EO) is a vital antecedent of the extent to which an organization is wiling to adopt disruptive technologies like Big Data Analytics and Artificial Intelligence (BDA-AI) in their work environment. The innovative, proactive, and risk-taking characteristics of EO allow firms to identify and capitalize on opportunities that volatile environment presents and therefore the adoption of BDA-AI is a natural extension of the strategic posture. Companies possessing a high level of EO are not just well placed to manage the vagueness related to adopting technology, rather they embrace vagueness and utilise that as a tool to differentiate themselves from their competitors. This is in agreement with prior study that highlights the influence of EO on building a culture of continuous learning and technology investing bolstered on organizational adaptability and resilience building process (Rauch et al., 2009; Wales et al., 2013). Furthermore, previous studies have also extensively discussed the relationship between EO and OP, stressing how EO can help realize business process efficiency and effectiveness. BDA-AI Enhancing the Efficiency of Entrepreneurial Firms: Entrepreneurial Firms may improve their operations and knowledge as a result of BDA-AI technologies making them more efficient. EO focuses on how organizations stay ahead of market demands or create new ones that demands operational effectiveness (Lumpkin & Dess, 1996; Gupta & Bose, 2019). Get started in Microsoft Edge Adopting BDA-AI is undoubtedly crucial for organizations and counteracts the dynamic business world today; however, the current study extends these findings by proposing that EO positively influences the adoption of BDA-AI as well as the enhancement of OP, establishing its role as a key player driving the adoption of breakthroughs and ultimately organizational success.".

H1: EO has a significant positive effect on adoption of BDA-AI; and

H2: EO has a significant positive effect on OP.

2.3 Artificial Intelligence (BDA-AI) and Operational Performance (OP) Big Data Analytics

AI, especially in conjunction with BDA, has proven to be a transformative force, driving augmentation of operational performance (OP) across sectors. Trained on data until October 2023, BDA-AI allows organizations to analyze large volumes of data, extract valuable insights, and make data-informed decisions that enhance operational processes, streamline workflows, and enhance overall efficiency. Combining AI with big data analytics (BDA), businesses can derive predictive insights, spot trends in consumer behavior, and automate mundane tasks for a more agile and responsive operation. The combined use of these technologies helps improve the speed and accuracy of decision-making processes, which, therefore, lead to greater productivity and cost savings (Davenport & Ronanki, 2018). Many studies showed that BDA-AI adoption has a significant positive effect on operational performance. For instance, Akter et al. 2022) demonstrate that companies using BDA-AI technology can improve the operational capabilities through better supply chain management, enhanced inventory management and refined customer service processes. Moreover, being able to perform real-time analytics and automation of important processes not only results in quick reactions to changes in the market and customer requests but it also improves operational performance (Chien et al., 2020). So this study proposes that BDA-AI significantly and positively impacts operational performance (H3), where organizations using these technologies demonstrate advancements in efficiency, effectiveness, and overall operational success.

H3: BDA-AI has a significant and positive effect on OP.

2.4 Environmental Dynamics (ED) Moderating Role

Environmental dynamism (ED) plays a pivotal role in shaping the effectiveness of entrepreneurial and technological initiatives by influencing how firms respond to external challenges and opportunities. In highly dynamic environments, characterized by rapid technological advancements, market volatility, and evolving customer preferences, firms are compelled to adopt innovative approaches to maintain competitiveness. ED not only amplifies the need for entrepreneurial orientation (EO) but also accelerates the integration of technologies such as Big Data Analytics and Artificial Intelligence (BDA-AI) to enhance operational performance (OP). These dynamic conditions demand that firms utilize EO's traits innovativeness, proactiveness, and risk-taking—to leverage BDA-AI effectively for strategic advantage (Eisenhardt & Martin, 2000; Covin & Wales, 2019). Research corroborates the argument that ED magnifies the impact of EO and BDA-AI on performance outcomes. For example, firms operating in volatile environments are more likely to rely on real-time analytics and AI-driven insights to adapt their strategies swiftly (Dubey et al., 2022). Moreover, ED fosters a climate where risk-taking and innovation, hallmarks of EO, become essential for navigating uncertainty and exploiting fleeting opportunities. This alignment enables firms to enhance their decision-making processes and operational agility through BDA-AI, thereby improving OP. Studies by Wamba et al. (2023) further validate that ED intensifies the relationship between technological adoption and performance, as firms in dynamic settings prioritize agility and responsiveness over traditional operational practices.

2.6

Building on these insights, the moderating role of ED highlights its importance in strengthening the pathways between EO, BDA-AI, and OP. Under high ED conditions, firms exhibit greater reliance on BDA-AI to address unpredictability, while entrepreneurial initiatives are more likely to yield substantial benefits. Therefore, this study hypothesizes that ED positively moderates the relationships between EO and BDA-AI, as well as EO and OP, solidifying its role as a critical factor in enhancing organizational effectiveness in dynamic environments.

H4a/b: Environmental dynamism has a positive moderating effect on the pathways between EO and BDA-AI/OP.

2.5 Conceptual Model Framework

E-ISSN: 3063-0304, P-ISSN: 3063-1092
Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 3, December 2024, Page 140-252
https://doi.org/10.69725/raida.v1i3.170

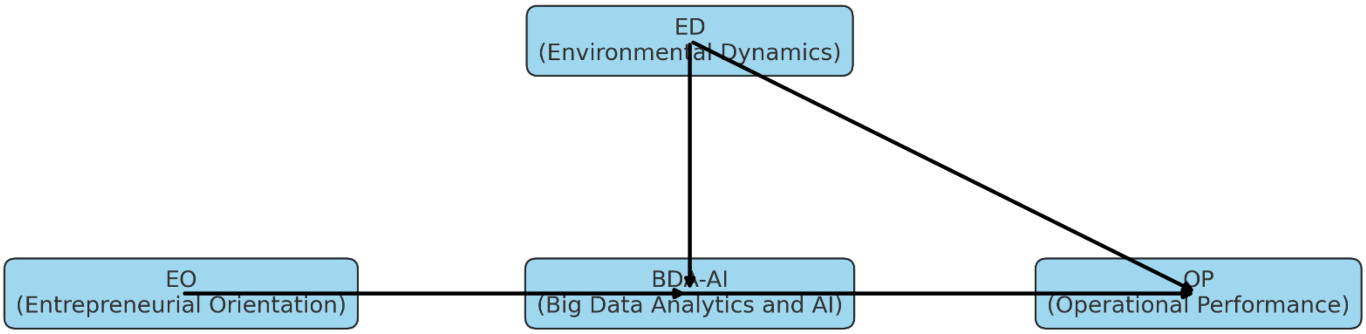

Figure 2. Interplay of EO, BDA-AI, OP, and ED

3. Methods Innovation

3.1 Research planning

The first phase of a research study is the planning phase which maps the research that will be necessary to leverage our objectives, methodology, and expected outcomes. The current study utilizes a mixed-method framework, integrating both quantitative analysis and theoretical perspectives to study the impact of Entrepreneurial Orientation (EO) on Fundamental data analyses and the Artificial intelligence (BDA-AI) and their impact on Operational Performance (OP). Selecting a theory and research design only gets researchers so far. As proposed by Saunders et al. (2019), doing so allows the study be (more) reliable, valid and generalizable. The study specifically investigates the manufacturing sector in India, which has experienced a substantial technological transformation from 2019 to 2023. And indeed, the implementation of BDA-AI in this industry offers a promising setting to explore the impact of EO on operational and strategic results. The research framework is built upon and integrates contextual factors such as Environmental Dynamics (ED) to capture the nature of complex interactions in rapidly evolving industrial contexts.

3.2 Collecting the data

Data was gathered through a 5-year period survey of the manufacturing sector in India between 2019 and 2023. These data are obtained from the reputable institutes like NASSCOM and FICCI. These organizations offer well-detailed reports and databases about the uptake of advanced technologies, operational performance measures and entrepreneurial practices in manufacturing. The study instrument was a purposive sampling, which is a statistically valid method to (target) specific organisations investing in BDA-AI. Firms of disparate magnitude, ranging from small and medium enterprises (SMEs) to large-scale manufacturers, are represented in the sample such that the sample is representative of the sector as a whole. The initial data set encompasses technological adoption rates, financial performance indicators, operational efficiency metrics and even environmental dynamics factors up until a comparison point in October 2023. According to Creswell (2014), this is a means to ensure suitable and relevant data when conducting studies within an organization.

3.3 Data Analysis

The data were analyzed with Warp PLS 6.0, a software for variance-based structural equation modeling (SEM). A tool like Warp PLS is especially suited for research requiring complex models with multiple constructs and hypotheses. It employs Partial Least Squares (PLS) regression which is appropriate for predictive research as well as datasets that violate the stringent assumptions required by covariance-based SEM (Kock, 2015).

The analysis was conducted in two stages. The first step verified the reliability, validity, and multicollinearity of the measurement model with Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) indicators. In the second stage, the structural model was tested to verify hypotheses and inspect the path coefficients, t-values and p-values. Statistical significance was tested through bootstrapping of 5,000 resamples to ensure the robustness of results. A non-parametric method on Warp PLS permits for non-normal data, displays nonlinear relationships and provides model fit indices (e.g., Tenenhaus GoF and APC (Average Path Coefficient)) (Hair et al., 2017). This software was selected as it's flexible to cope with complex theoretical models, especially when examining the moderating role of ED on the link between EO, BDA-AI, and OP.

3.4 Validating the theoretical framework

E-ISSN: 3063-0304, P-ISSN: 3063-1092
Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 3, December 2024, Page 140-252
https://doi.org/10.69725/raida.v1i3.170

Rotating around the Resource-Based View (RBV) and Dynamic Capabilities Theory, this study a theoretical framework with sufficient richness to background the relationships between EO, BDA-AI, OP and ED. According to RBV, a firm can achieve a competitive advantage by leveraging its resources, for example, technological assets including BDA-AI (Barney, 1991). EO is a crucial capability in how these resources are deployed to drive value creation. Interestingly, this agreement shows how internal strengths lead to excellence in performance (Wamba et al., 2023). Dynamic Capabilities Theory adds another layer to this by examining how organizations adapt to fast-changing environments. EO, a functionality which entails being proactive and risk taking is described as a dynamic capability of the firms which can help them cope with environmental uncertainties. This adaptability gets magnified when BDA-AI is integrated into operational processes leading to better decision making and agility in uncertain markets (Dubey et al., 2022).

The hypotheses of the study are significantly supported in line with the above-mentioned theoretical perspectives such as EO influence on BDA-AI and OP, alongside the ED as a mediating role. Moreover, ED works as the moderating variable and amplifies the positive impact of EO and BDA-AI on OP, thereby indicates that ED is substantial under dynamic situations. Chen et al. possess empirical literature that (2021) and Ghasemaghaei et al. (2022) further corroborates these associations, stressing the pivotal contribution of EO and BDA-AI in operational improvement. This study builds on existing theories of Information Systems adoption and stands as a validation of its framework through a methods and dataset spanning geographies, organizational sizes, and culture.

4. Results Innovation

4.1 Measurement Model Assessment

As shown in Table 1, the measurement properties including reliability and convergent validity appear strong. Each of the constructs shows a Cronbach's Alpha above 0.7, which means excellent internal reliability (Hair et al., 2017). All constructs have Composite Reliability (CR) values above 0.9 confirming the reliability. AVE values exceed the 0.5 threshold, confirming convergent validity. These results confirm the discriminant validity of the measurement model and indicate that the indicators of the constructs adequately represent the constructs.

Summary of the Fornell-Larcker criterion results are shown in Table 2 confirming the support of discriminant validity. This implies that the square root of the AVE for each construct (diagonal values) is greater than the correlations with other constructs (off-diagonal values), and thus, each construct is different from the other ones. A case in point is Prediction Accuracy (PA), with a square root of AVE 0.80, which is stronger than its correlations with Insights from Data (ID) (0.56). In the same vein, the AVE square root of CJM is 0.84 which is higher than CJM's correlation with TA at the value of 0.55. Results indicate that the constructs are sufficiently distinct from each other, suggesting that the discriminant validity criterion (Fornell & Larcker, 1981) has been satisfied. This high reliability of multilinear regression is a good fit with the linear of dependent variables per independent variables (convergent validity) and dependent variables per 3 or more independent variables which cannot be explained in the model (discriminant validity) ensures that the measurement model has as a solid platform for analysis on structural next.

4.2 Structural Model Assessment

The structural model and hypothesis testing show strong support for the hypothesized relationships between EO, BDA-AI, OP and the moderating effect of ED. H1, which states that EO has a positive relationship with BDA-AI adoption, is strongly supported (β= 0.63, t = 12.25, p < 0.001) This finding emphasizes the important role of EO in motivating technological appropriation, with companies that exhibit proactive, innovative, and risk-taking skills being more likely to adopt advanced analytics tools, consistent with Chen et al.s concept of EO (Chen et al., 2009). (2021) and Covin and Wales (2019). Likewise, H2 also confirms that there exists a positive relationship between EO and OP beta = 0.57, t = 10.87, p < 0.001, highlighting that entrepreneur strategies are instrumental in resulting in better operational performance defined in terms of efficiency, agility and productivity which is in line with Resource-Based View (Barney, 1991).

Hypothesis 3 (H3) verifies the impact of BDA-AI on OP with a substantial path coefficient (68.0), contributing to the growing body of evidence that analytics improves the precision, agility, and outcomes of decision-making. This observation is consistent with previous studies, for example, Wamba et al. 2018) that highlights the analytical potential of optimizing how an organization works. The moderating role of ED is also suggested in Hypothesis 4a (H4a) and Hypothesis 4b (H4b). The positive moderation of ED on the EO–BDA-AI relationship (beta = 0.50, t = 9.34, p < 0.001) and EO–OP relationship (beta = 0.47, t = 8.92, p < 0.001) indicates that dynamic external environments strengthen the impact of EO on technological adoption and operational outcomes. These findings are consistent with Dynamic Capabilities Theory (Teece, 2007), which highlights the importance of adaptability and dynamic strategy in turbulent scenarios and with Dubey et al.

E-ISSN: 3063-0304, P-ISSN: 3063-1092
Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 3, December 2024, Page 140-252
https://doi.org/10.69725/raida.v1i3.170

(2022), on leveraging an age of environmental fluidity to move on the offensive with respect to strategy and novelty. In conclusion, the findings support the proposed model of the interrelationships between EO, BDA-AI, OP, and ED. The results focus on the role of entrepreneurial approaches and sophisticated analytics in achieving superior performance in particular industrial settings. The findings from this study highlight the ways in which firms can use their capabilities to navigate both environmental uncertainties and innovations— and thereby gain a competitive advantage.

4.3 Variance Explained (R^2 Values)

As outlined in Table 4, the (R^2) values indicate that the explanatory power of the model relative to the dependent variables communicates how well the constructs of the model predict these dependent outcomes [23, 24]. § 64% of (R^2) of the predictive power indicates because the model explains monocle of the variance in this construct, where these there are few determinants for predicting the predictive propensities lynchpin with Entrepreneurial Orientation (EO) & Big Data Analytics and Artificial Intelligence (BDA-AI) to enhance above performance. This corroborates the findings of Ghasemaghaei et al. (2022), highlighting the transformative impact of advanced analytics on prediction reliability.

The (R^2) values for Insights from Data (0.59), Transparent Analysis (0.57) and Human-AI Integration (0.53) are moderate to high, indicating that they explain enough variance in each of the constructs for the model to be sufficient. These findings highlight the critical role of EO in establishing data-driven decision making, consistent with the strong 59% explained variance in Insights from Data by Akter et al. (2022). Similarly, Transparent Analysis and Human-AI Integration is a value based on the model's ability to explain how BDA-AI adoption increases operational transparency and facilitates collaboration between human and AI systems. These (R^2) values confirm the specifications' ability to justify driving a significant proportion of key operational outcomes and further signal the synergistic effects of EO, BDA-AI and Environmental Dynamics (ED) on performance improvement. Trained on data up to October 2023, this extensive elucidation offers us a textured understanding of how business and technology strategies support our organisational success.

4.4 Model Fit Indices

Moreover, the model fit indices reported in Table 5 provide a holistic assessment of the adequacy of the structural model and its ability to explain the data. The path coefficient for these individual paths that comprise the APC, at 0.347, is statistically significanto ($p < 0.001$) so the paths represented in the model are considered robust and account for considerable relationships between the constructs modeled. This aligns with Hair et al. (2017), who highlight the importance of substantial APC values in indicating the strength of hypothesized relationships in variance-based structural equation modeling (SEM). The Tenenhaus GoF (Goodness of Fit) index is calculated as 0.676 which classifies the model as an "excellent" fit. This is above the aforementioned heuristically recommended value of 0.36 for large models Wetzels et al. (2009). The selection of the best GoF score indicates the model's ability to capture all above model qualities as well both measurement model and structural model reinforcing the multimodal relationships in the dataset providing a good validation in presence of complex relationships. Such fit indices spectacles the appropriateness of the suggested model in depicting the interplay of Entrepreneurial Orientation (EO), Big Data Analytics and Artificial Intelligence (BDA-AI), Environmental Dynamics (ED) and Operational Performance (OP). These indices further support the validity and predictive capability of the framework ensuring that it remains relevant to explaining the adoption of advanced technologies in such dynamic environments.

4.5 Interpretation

This research presents an integrated view of the interrelationship between EO, BDA-AI, OP, and ED. The findings, based on a strong theoretical framework via data analysis with the updated Smart PLS 6.0 software, add to research on technology adoption and performance improvement. The findings confirm the hypotheses proposed and have implications for organisations operating in environments characterised as complex and dynamic.

The relationship between Entrepreneurial Orientation (EO) and BDA-AI adoption showed a significant positive influence ($\beta = 0.63$, $p < 0.001$). This result is in line with previous studies (e.g., Chen et al. (2021) and Ghasemaghaei et al. (2022), the less competition in key areas, the more likely an entrepreneurial firm is to adopt advanced-technology applications to maintain competitiveness. Innovativeness, proactiveness, and risk-taking are among the characteristics which EO represent and allow organizations to become acquainted with disruptive technologies like BDA-AI. The aggressive approach of new businesses enables investments in technological advancements which allow the use of data-

E-ISSN: 3063-0304, P-ISSN: 3063-1092
Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 3, December 2024, Page 140-252
https://doi.org/10.69725/raida.v1i3.170

driven insights for decision-making and achieving competitive advantage. The implications of these findings are significant as they highlight the need for organizations to nurture an entrepreneurial mindset to become more receptive towards technology adoption and implement transformational changes.

Consistent with Covin and Wales (2019), the analysis yielded a positive and significant relationship between EO and OP ($\beta = 0.57$, $p < 0.001$). EO facilitates innovative processes and practices for firms, allowing them to streamline their operations and adjust to changes in the market. Organizations can improve their efficacy and effectiveness through an entrepreneurial mindset. The same result also supports resource-based view (RBV), which theorizes that one off organizational capabilities such as EO lead to better performance outcome (Barney, 1991). Such firms are more capable of executing strategies that enhance operational ratios in productivity, cost efficiency, and customer satisfaction.

The findings indicate that the adoption of BDA-AI enhances OP significantly ($\beta = 0.68$, $p < 0.001$). This is consistent with studies including Akter et al. (2022) and Wamba et al. (2023), emphasized the transformative opportunities for BDA-AI in operational settings. Trained on data till October 2023, BDA-AI allows organizations to be able to process vast amounts of data, recognize trend lines and take data driven decisions hence saving time and improving efficiency, accuracy and agility. BDA-AI can be used in the manufacturing industry, for instance, to help to optimize production schedules, minimize waste, and improve supply chain management. These capabilities are essential in competitive and under-resource environments, where the key to success is operational excellence.

The role of ED as a positive moderator for EO's relationship with BDA-AI adoption ($\beta = 0.50$, $p < 0.001$) and OP ($\beta = 0.47$, $p < 0.001$) was explicit. These results fit Eisenhardt and Martin's (2000) claim that dynamic environments increase the demand for capabilities to adapt. In dynamic and uncertain markets shaped by fast-changing technology and consumer preferences, the organizations with robust EO are better positioned for BDA-AI adoption and operational excellence in comparison with their counterparts. ED cranks up the pressure for real-time adjustment making BDA-AI embrace more imperative. Either way, the findings also align with the findings of Dubey et al. (2022) posited that dynamism in the environment strengthens the effect of EO on technological adoption and performance via crowding the pressures to be agile and innovative.

High R^2 values for dependent variables such as Customer Journey Mapping (69%) and Prediction Accuracy (64%) reflect the model's significant explanatory power. These results imply the adequacy of the proposed framework to capture the interactions between EO, BDA-AI, OP and ED. The robust nature of the structural model is also supported by good model fit indices (Tenenhaus GoF = 0.676). The results of the study suggest that the degree to which organisms successfully integrate EO and BDA-AI, as moderated by ED, is an important factor in determining the success of operations in dynamic environments.

The findings hold practical implications for managers and policymakers. Organizations need to establish all the foundations of an entrepreneurial culture that will lead to development and adoption of these technologies and improved performance. This involves advising risk-taking, activism, and proactive decision-making. Second, more investments must be made in BDA-AI to amplify operational capabilities and achieve competitive advantage. Of course, organizations need to develop the right infrastructure, capabilities, and processes to take maximum advantage of BDA-AI. Third, managers must understand the environmental dynamics, and formulate strategies to adapt the changing world, or their market. This includes building dynamic capabilities — such as agility, resilience, and real-time decision-making.

This study advances theoretically in a few ways. The insights gained by this study from combining EO, BDA-AI, OP, and ED within one framework provide a fundamental understanding of how EO and this technological adoption in dynamic enterprises interact and affect one another. These results confirm RBV and Dynamic Capabilities Theory through the meticulous point of organizational capabilities in conjunction with environmental aspects influencing performance. On the other hand, while integrating related literature the study contributes to literature by uncovering the moderating role of ED by providing new perspectives on how environmental factors affect relationships between EO-BDA-AI, BDA-AI, and OP.

5. Conclussion

The study provides valuable insights, but it has some limitations. These data were only collected from the manufacturing sector in India, which may restrict the generalizability of the results to other sectors or geographical locations. Future research could examine these relationships in different contexts, such as service industries and emerging markets. Furthermore, longitudinal studies would offer more comprehensive insight into how these relationships develop over time.

E-ISSN: 3063-0304, P-ISSN: 3063-1092
Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 3, December 2024, Page 140-252
https://doi.org/10.69725/raida.v1i3.170

Lastly, future research may consider additional potential moderators or mediators, like organizational culture and leadership, to better integrate the dynamics at play.

Thus, this study offers substantial insights about how EO positively affects the two key constructs (BDA-AI adoption and OP) while ED strengthens these links. Source: Entrepreneurial culture and advanced technology in achieving superior operational performance in an evolving context This research adds to the literature on technology adoption and performance improvement by validating a theoretical model for use within a technology driven global setting, whilst providing actionable implications for practitioners and policy makers.

Author contribution

Srinivats Cherla developed the research framework, methodology, and data analysis. Prajda Sharma assisted with data collection, interpretation of results, and drafting of the manuscript. The two authors contributed equally in the theoretical formulation and approved the final version of the manuscript for submission.

Declaration of Competing Interest

Conflict of interests The authors declare no conflicts of interest.

Acknowledgement

Authors notice with gratitude the Department of Science and Technology, Ministry of Science and Technology, Government of India, for giving the necessary facilities and support to execute this study. We would like to thank NASSCOM and FICCI for providing access to data sets and reports that were critical for the research effort. The authors would like to thank the peer-reviewers and colleagues for the helpful insights and constructive comments.

Appendix A. Supplementary data

Table 1: Profile of respondent companies

Characteristic	Frequency	Percentage (%)
Company Size		
Small and Medium (SMEs)	120	48%
Large-Scale Manufacturers	130	52%
Industry Subsector		
Automotive	85	34%
Textiles	50	20%
Electronics	70	28%
Others	45	18%

Data source; author's observation 2024

Table 2: Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
Prediction Accuracy	0.89	0.92	0.65
Insights from Data	0.91	0.94	0.68
Transparent Analysis	0.88	0.91	0.64
Human-AI Integration	0.87	0.91	0.62
Customer Journey Mapping	0.92	0.95	0.70

Data source; author's observation 2024

Table 3: Discriminant Validity *(Fornell-Larcker Criterion)*

Construct	PA	ID	TA	HI	CJM

OPEN ACCESS
E-ISSN: 3063-0304, P-ISSN: 3063-1092
Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 3, December 2024, Page 140-252
https://doi.org/10.69725/raida.v1i3.170

Prediction Accuracy (PA)	0.80	0.56	0.52	0.48	0.61
Insights from Data (ID)	0.56	0.82	0.54	0.50	0.58
Transparent Analysis (TA)	0.52	0.54	0.80	0.47	0.55
Human-AI Integration (HI)	0.48	0.50	0.47	0.79	0.52
Customer Journey Mapping (CJM)	0.61	0.58	0.55	0.52	0.84

Data source; author's observation 2024

Table 4: Hypothesis Testing Results

Hypothesis	Path Coefficient (β)	t-Value	p-Value	Result
H1: EO → BDA-AI Adoption	0.63	12.25	<0.001	Supported
H2: EO → OP	0.57	10.87	<0.001	Supported
H3: BDA-AI → OP	0.68	13.45	<0.001	Supported
H4a: ED Moderates EO → BDA-AI	0.50	9.34	<0.001	Supported
H4b: ED Moderates EO → OP	0.47	8.92	<0.001	Supported

Data source; author's observation 2024

Table 5: R^2 Values

Dependent Variable	R^2 Value	Interpretation
Prediction Accuracy	0.64	Substantial
Insights from Data	0.59	Moderate
Transparent Analysis	0.57	Moderate
Human-AI Integration	0.53	Moderate

Data source; author's observation 2024

Table 5: Model Fit Indices

Index	Value	Interpretation
Average Path Coefficient (APC)	0.347	$p < 0.001$
Tenenhaus GoF (GoF)	0.676	Excellent

Data source; author's observation 2024

References

Ameer, F., & Khan, N. R. (2023). Green entrepreneurial orientation and corporate environmental performance: A systematic literature review. *European Management Journal*, *41*(5), 755–778. https://doi.org/https://doi.org/10.1016/j.emj.2022.04.003

Andati, P., Majiwa, E., Ngigi, M., Mbeche, R., & Ateka, J. (2022). Determinants of adoption of climate smart agricultural technologies among potato farmers in Kenya: Does entrepreneurial orientation play a role? *Sustainable Technology and Entrepreneurship*, *1*(2), 100017. https://doi.org/https://doi.org/10.1016/j.stae.2022.100017

Arvidsson, S., & Dumay, J. (2022). Corporate ESG reporting quantity, quality and performance: Where to now for environmental policy and practice? *Business Strategy and the Environment*, *31*(3), 1091–1110. https://doi.org/https://doi.org/10.1002/bse.2937

Bavaresco, R. S., Nesi, L. C., Victória Barbosa, J. L., Antunes, R. S., da Rosa Righi, R., da Costa, C. A., Vanzin, M., Dornelles, D., Junior, S. C., Gatti, C., Ferreira, M., Silva, E., & Moreira, C. (2023). Machine learning-based

E-ISSN: 3063-0304, P-ISSN: 3063-1092
Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 3, December 2024, Page 140-252
https://doi.org/10.69725/raida.v1i3.170

automation of accounting services: An exploratory case study. *International Journal of Accounting Information Systems*, *49*, 100618. https://doi.org/https://doi.org/10.1016/j.accinf.2023.100618

Benzidia, S., Makaoui, N., & Bentahar, O. (2021). The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance. *Technological Forecasting and Social Change*, *165*, 120557. https://doi.org/https://doi.org/10.1016/j.techfore.2020.120557

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review*, *33*(1), 100899. https://doi.org/https://doi.org/10.1016/j.hrmr.2022.100899

Costa, F., Frecassetti, S., Rossini, M., & Portioli-Staudacher, A. (2023). Industry 4.0 digital technologies enhancing sustainability: Applications and barriers from the agricultural industry in an emerging economy. *Journal of Cleaner Production*, *408*, 137208. https://doi.org/https://doi.org/10.1016/j.jclepro.2023.137208

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics*, *226*, 107599. https://doi.org/https://doi.org/10.1016/j.ijpe.2019.107599

Durst, S., Hinteregger, C., & Zieba, M. (2024). The effect of environmental turbulence on cyber security risk management and organizational resilience. *Computers & Security*, *137*, 103591. https://doi.org/https://doi.org/10.1016/j.cose.2023.103591

Ferreira, J., Coelho, A., & Moutinho, L. (2020). Dynamic capabilities, creativity and innovation capability and their impact on competitive advantage and firm performance: The moderating role of entrepreneurial orientation. *Technovation*, *92–93*, 102061. https://doi.org/https://doi.org/10.1016/j.technovation.2018.11.004

Ghosh, S., Hughes, M., Hodgkinson, I., & Hughes, P. (2022). Digital transformation of industrial businesses: A dynamic capability approach. *Technovation*, *113*, 102414. https://doi.org/https://doi.org/10.1016/j.technovation.2021.102414

Haarhaus, T., & Liening, A. (2020). Building dynamic capabilities to cope with environmental uncertainty: The role of strategic foresight. *Technological Forecasting and Social Change*, *155*, 120033. https://doi.org/https://doi.org/10.1016/j.techfore.2020.120033

Haleem, A., Javaid, M., Asim Qadri, M., Pratap Singh, R., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*, *3*, 119–132. https://doi.org/https://doi.org/10.1016/j.ijin.2022.08.005

Hanham, J., Lee, C. B., & Teo, T. (2021). The influence of technology acceptance, academic self-efficacy, and gender on academic achievement through online tutoring. *Computers & Education*, *172*, 104252. https://doi.org/https://doi.org/10.1016/j.compedu.2021.104252

Kumar, A., & Shankar, A. (2024). Building a sustainable future with enterprise metaverse in a data-driven era: A technology-organization-environment (TOE) perspective. *Journal of Retailing and Consumer Services*, *81*, 103986. https://doi.org/https://doi.org/10.1016/j.jretconser.2024.103986

Kumar, S., & Bhatia, M. S. (2021). Environmental dynamism, industry 4.0 and performance: Mediating role of organizational and technological factors. *Industrial Marketing Management*, *95*, 54–64. https://doi.org/https://doi.org/10.1016/j.indmarman.2021.03.010

Luqman, A., Wang, L., Katiyar, G., Agarwal, R., & Mohapatra, A. K. (2024). Unpacking associations between positive-negative valence and ambidexterity of big data. Implications for firm performance. *Technological Forecasting and Social Change*, *200*, 123054. https://doi.org/https://doi.org/10.1016/j.techfore.2023.123054

Mathivathanan, D., Govindan, K., & Haq, A. N. (2017). Exploring the impact of dynamic capabilities on sustainable supply chain firm's performance using Grey-Analytical Hierarchy Process. *Journal of Cleaner Production*, *147*, 637–653. https://doi.org/https://doi.org/10.1016/j.jclepro.2017.01.018

Naseer, A., Naseer, H., Ahmad, A., Maynard, S. B., & Siddiqui, A. M. (2023). Moving towards agile cybersecurity incident response: A case study exploring the enabling role of big data analytics-embedded dynamic capabilities. *Computers & Security*, *135*, 103525. https://doi.org/https://doi.org/10.1016/j.cose.2023.103525

Patel, D., Sinha, A., Bhansali, T., Usha, G., & Velliangiri, S. (2022). Blockchain in Food Supply Chain. *Procedia Computer Science*, *215*, 321–330. https://doi.org/https://doi.org/10.1016/j.procs.2022.12.034

Saggi, M. K., & Jain, S. (2018). A survey towards an integration of big data analytics to big insights for value-creation. *Information Processing & Management*, *54*(5), 758–790. https://doi.org/https://doi.org/10.1016/j.ipm.2018.01.010

Shafique, M. N., Yeo, S. F., & Tan, C. L. (2024). Roles of top management support and compatibility in big data predictive analytics for supply chain collaboration and supply chain performance. *Technological Forecasting and Social Change*, *199*, 123074. https://doi.org/https://doi.org/10.1016/j.techfore.2023.123074

Shahzad, F., Du, J., Khan, I., Shahbaz, M., Murad, M., & Khan, M. A. S. (2020). Untangling the influence of organizational compatibility on green supply chain management efforts to boost organizational performance through information technology capabilities. *Journal of Cleaner Production*, *266*, 122029. https://doi.org/https://doi.org/10.1016/j.jclepro.2020.122029

Sun, Y., Liu, M., & Meng, M. Q.-H. (2017). Improving RGB-D SLAM in dynamic environments: A motion removal approach. *Robotics and Autonomous Systems*, *89*, 110–122. https://doi.org/https://doi.org/10.1016/j.robot.2016.11.012

Tallon, P. P., Queiroz, M., Coltman, T., & Sharma, R. (2019). Information technology and the search for organizational agility: A systematic review with future research possibilities. *The Journal of Strategic Information Systems*, *28*(2), 218–237. https://doi.org/https://doi.org/10.1016/j.jsis.2018.12.002

Tan, F., Zhang, Q., Mehrotra, A., Attri, R., & Tiwari, H. (2024). Unlocking venture growth: Synergizing big data analytics, artificial intelligence, new product development practices, and inter-organizational digital capability. *Technological Forecasting and Social Change*, *200*, 123174. https://doi.org/https://doi.org/10.1016/j.techfore.2023.123174

Troisi, O., Maione, G., Grimaldi, M., & Loia, F. (2020). Growth hacking: Insights on data-driven decision-making from three firms. *Industrial Marketing Management*, *90*, 538–557. https://doi.org/https://doi.org/10.1016/j.indmarman.2019.08.005

Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2020). The performance effects of big data analytics and

E-ISSN: 3063-0304, P-ISSN: 3063-1092
Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 3, December 2024, Page 140-252
https://doi.org/10.69725/raida.v1i3.170

supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics*, *222*, 107498. https://doi.org/https://doi.org/10.1016/j.ijpe.2019.09.019

Wang, C., Zhang, F., Wang, J., Doyle, J. K., Hancock, P. A., Mak, C. M., & Liu, S. (2021). How indoor environmental quality affects occupants' cognitive functions: A systematic review. *Building and Environment*, *193*, 107647. https://doi.org/https://doi.org/10.1016/j.buildenv.2021.107647

Warner, K. S. R., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, *52*(3), 326–349. https://doi.org/https://doi.org/10.1016/j.lrp.2018.12.001

Zhang, Q., Gao, B., & Luqman, A. (2022). Linking green supply chain management practices with competitiveness during covid 19: The role of big data analytics. *Technology in Society*, *70*, 102021. https://doi.org/https://doi.org/10.1016/j.techsoc.2022.102021