Complex interplay of R&D, advertising and exports in USA manufacturing firms: differential effects of capabilities

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Abstract
Purpose – This study aims to explore the dynamic interplay of key resources (i.e. research and development (R&D), advertising and exports) in affecting the performance of USA manufacturing firms. Specifically, the authors examine the dynamic impact of joint resources and predict differential effect scales contingent on firm capabilities.

Design/methodology/approach – This study presents a combined multiple regression analysis (MRA)-multilayer perceptron (MLP) neural network modeling and investigates the complex interlinkage of capabilities, resources and performance. As an innovative approach, the MRA-MLP model investigates the effect of capabilities under the combinatory deployment of joint resources.

Findings – This study finds that the impact of joint resources and synergistic rents is not uniform but rather distinctive according to the combinatory conditions and that the pattern is further shaped by firm capabilities. Accordingly, besides signifying the contingent aspect of capabilities across a range of resource combinations, the result also shows that managerial sophistication in adaptive resource control is more than a managerial ethos.

Practical implications – The proposed analytic process provides scientific decision support tools with control mechanisms with respect to deploying multiple resources and setting actionable goals, thereby presenting pragmatic benchmarking options to industry managers.

Originality/value – Using the theoretical underpinnings of the resource-based view (RBV) and resource orchestration, this study advances knowledge about the complex interaction of key resources by presenting a salient analytic process. The empirical design, which portrays holistic interaction patterns, adds to the uniqueness of this study of the complex interlinkages between capabilities, resources and shareholder value.

Keywords Advertising, Capabilities, Exports, R&D, Neural network

1. Introduction
The prudent allocation of strategic resources to support technological innovation and improve export performance has been a managerial challenge for manufacturing firms competing in international markets. Although a firm’s emphasis on exports, investments in advertising, and spending on research and development (R&D) are seen as important contributors to firm performance (Carboni and Medda, 2020; Cassiman and Golovko, 2011; Golovko et al., 2022; Makrini, 2017), mainstream research has neglected the interaction effects of these contributors on firm performance. As a result, little is known about the synergistic interplay of R&D, advertising and export operations and their impact on performance at different levels of firm capabilities. The present study thus addresses an important managerial dilemma – the need to optimize levels of R&D, advertising and exports in an
environment in which a firm’s capabilities may shape the outcome of these three factors’ synergistic interplay on its performance.

Advertising and research and development (R&D) are commonly viewed as intangible assets, with the former contributing to relational market-based assets for improved brand awareness and the latter playing a leading role in the development of intellectual assets for knowledge creation (Peterson and Jeong, 2010; Sharma and Lichtenthal, 2023; Srivastava et al., 1998; Yang et al., 2015). Both advertising and R&D are also treated as complementary assets from a value-formulating perspective vis-à-vis value appropriation and value creation, thereby affecting shareholder values (Mizik and Jacobson, 2003). Similarly, the interplay of R&D and exports is often explained by the theoretical framework of “learning-by-exporting” (LBE) (Cassiman and Golovko, 2011; Golovko et al., 2022; Segarra-Blasco et al., 2022).

According to LBE, investment in R&D is a precondition for successfully entering foreign markets, and the spillovers from post-entry knowledge enhance the innovation capabilities of exporting firms, thereby enhancing their performance in international markets (Cassiman and Golovko, 2011; Golovko et al., 2022). Export performance is also known to have interactive relationships with branding capabilities in cases in which advertising plays a significant role, which also enhances firms’ performance in international markets. In line with the resource-based view (RBV), export performance is expected to increase upon the deployment of complementary assets in marketing and R&D (Gupta and Chauhan, 2021; Hitt et al., 2006; Theodosiou et al., 2012; Yang et al., 2015). In brief, the three resources (R&D, advertising and exports) are closely related in the value-formulation process, which includes value creation (R&D), value appropriation (advertising) and knowledge acquisition (exports). They are related, moreover, with respect to the technical and social expectations that emerge through encounters with the diverse demands of buyers in foreign markets, forming a virtuous circle (Gupta and Chauhan, 2021; Masso and Vahter, 2015; Mizik and Jacobson, 2003).

A body of research has investigated how investments in advertising, R&D expenditures and exports have contributed to performance (e.g. Beauchamp et al., 2020; Hughes et al., 2018; Joshi and Hanssens, 2009; Krasnikov and Jayachandran, 2008; Lee and Kwon, 2021; Luo, 2008; Luo and de Jong, 2012; Sridhar et al., 2014; Srinivasan et al., 2009). However, few studies have looked at the potential synergistic effects on shareholder value of joint investments in R&D, advertising and exports (Lee and Kwon, 2021; Love and Roper, 2015; Ren et al., 2015). Moreover, previous research has ignored the possibility that a firm’s current shareholder valuation (which is proxied by capabilities in this study) – as a functional output (i.e. Tobin’s Q) from expended aggregate resources – might moderate the potential synergistic effects (Doloreux et al., 2018; Hsiao et al., 2021; Hughes et al., 2018; Makrini, 2017; Morales et al., 2019). This study focuses on these shortcomings and has the unique objective of exploring the complex interlinkage of capabilities-resources-shareholder value, with a primary emphasis on quantifying the synergistic interactions between R&D, advertising and exports and shedding light on their effects on shareholder value. Specifically, this study seeks answers to the following sequential questions:

1. What is the relationship between the three resources (i.e. advertising, R&D and exports) and shareholder value (Tobin’s Q)?

2. To what extent does each resource impact shareholder value? In addition, do these impacts vary in accordance with the level of firm capabilities, whether high or low?

3. To what extent does the simultaneous deployment of combined resources (i.e. advertising and R&D; R&D and exports; exports and advertising) affect shareholder value? Does the synergistic rent vary in accordance with the level of firm capabilities?
As specified in these research questions, this study proposes a unique exploration of the complex linkage between resources and performance, with particular attention to capabilities as a differentiator. While the first question, as a preliminary investigation, is centered on explanatory analysis to determine the statistical significance of individual variables, the second and third questions are directed more toward predictive analytics and aim to score the comparative importance of advertising, R&D and exports, as well as to identify and retrieve their interplay patterns in association with capabilities.

Research on resource allotment and firm performance has been driven primarily by the RBV as its theoretic basis, which spotlights firm-specific resources and their deployment as a primary factor in reshaping a firm’s competitive stance, which may lead to superior performance (Barney et al., 2021; Helfat and Peteraf, 2003; Hughes et al., 2018). The RBV postulates that resources and capabilities are the primary source of a firm’s competitive advantage; however, the mere stock of resources and the allocation of individual resources in isolation may not be sufficient for a sustained competitive advantage. An optimal combination of resources and their agile deployment must be a prelude to superior performance in a competitive market environment (Gupta and Chauhan, 2021; Kumar and Rodrigues, 2020; Padgett and Galan, 2010). Indeed, as highlighted in recent studies (Hughes et al., 2018; Martin et al., 2017; Sirmon et al., 2007), harmonized resources become more valuable due to their synergistic effect and are less vulnerable to imitation than isolated resources. Hence, within the RBV framework, this study explores an intriguing research question on the complementarity and synergistic interplay of combined resources under varying capabilities in terms of shareholder valuation. Capabilities, with a min-max frame of resource (input) minimization and performance (output) maximization, were often treated as an intermediate asset interlinking resources and business outcomes (Ayabakan et al., 2017; Dutta et al., 2005; Yang et al., 2015). As Gupta and Chauhan (2021) assert, capabilities are deeply embedded in firm routines and procedures and are not easily visible to competitors, but the Blackbox-type processing mechanism of capabilities makes analysis a cumbersome task, and there has been a call for the development of an objective metric of capabilities (Ayabakan et al., 2017; Helfat and Winter, 2011; Shilke et al., 2018; Teece, 2014). Consequently, there is still a dearth of research on the synergistic effect under varying capabilities, especially for large manufacturing firms (Kumar and Rodrigues, 2020).

In coping with such a challenging research issue, this study responds to the need for an innovative analytic paradigm rather than solely relying on explanatory statistical analysis. Hence, we propose a combined parametric-nonparametric approach: multiple regression analysis (MRA) in the first stage (Question 1) as a preliminary analysis, followed by predictive analysis using a multi-perceptron neural network (MLP) in the subsequent stages (Questions 2 and 3). Assuming that Questions 2 and 3 necessitate a complex predictive mechanism for synergy analytics, MLP’s premise of adaptive learning without a priori assumptions is taken as a core methodological foundation. Moreover, what is unique to this study is that the MLP lays out a prospective methodological basis for segmenting firms in accordance with relative capabilities. Hence, this study’s contributions are both theoretical and methodological, and it expands our knowledge of the dynamic interplay of R&D, advertising and exports through an innovative empirical design and analytic scheme. From a pragmatic perspective, this study is expected to enhance managerial proficiency in allocating resources through scientific resource options rather than through the deployment of intuitive decision-making and heuristics.

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature, Section 3 introduces the analytic methods and process, Section 4 presents the empirical results and discussion and Section 5 concludes by presenting the study’s implications and limitations.
2. Literature review
2.1 Firm capabilities

A firm’s capabilities and efficient utilization of scarce resources are considered one of its core competencies and one that affects shareholder value. According to Dutta et al. (2005), “capabilities are conceived as the efficiency with which a firm employs a given set of resources (inputs) at its disposal to achieve certain objectives (outputs).” Such a min-max metric of capabilities is in line with the theoretic lens of the RBV, and the scalar measure of relative ratios is expected to represent the objective levels of firms’ transformative abilities to convert multiple inputs into desirable performance outcomes. From the RBV perspective, capabilities are treated as an intermediate asset, which is closely linked to market capitalization and shareholder value, thereby giving firms an advantageous position (Ayabakan et al., 2017; Gupta and Chauhan, 2021; Dutta et al., 2005; Sony et al., 2023; Yang et al., 2015). Emphasizing the intermediary role of firm-specific capabilities, Gupta and Chauhan (2021) posit that capabilities are a sustainable resource that is not easily interpreted by competitors, thereby making the firm’s process a Blackbox-type complex system. In this sense, capabilities synthesize firm resources for optimal value creation and appropriation, which shapes the effect scale of the firm’s strategic initiatives in technological innovation, marketing and international expansion (Ayabakan et al., 2017; Helfat and Winter, 2011; Shilke et al., 2018; Yang et al., 2015).

A number of researchers have noted that the effect of R&D investment on performance is causally ambiguous, mainly due to the intangible nature of R&D and the complicated value-formulation mechanism (Shilke et al., 2018; Teece, 2014). Likewise, export operations in a highly volatile and rapidly changing international market require a purposeful adaptation of resources to swiftly adjust to fluctuating market conditions and changing consumer demands (Gupta and Chauhan, 2021; Golovko et al., 2022; Hughes et al., 2018). Hence, a firm’s distinctive capability to assess market dynamics and orchestrate and reconfigure its resources for a competitive advantage is seen as a precondition for favorably synergizing the effect of investments on technological innovation and export operations along with marketing activities (Gupta and Chauhan, 2021; Yang et al., 2015). Indeed, capabilities significantly improve the effect of export operations, which may also boost R&D performance through mutual interactions, as seen in recent empirical studies of manufacturing firms (Carboni and Medda, 2020; Gupta and Chauhan, 2021; Ren et al., 2015; Zhang and Xie, 2020). In a similar vein, with the notion that a high volume of R&D investment does not always lead to innovation outcomes and that the optimal level of R&D investment is uncertain, the conversion of R&D resources to effective outcomes necessitates capabilities as a meta-resource to synergize R&D productivity in association with marketing efforts (Lin et al., 2006; Yu et al., 2018). In this sense, capabilities can account for inter-firm variance in the effectiveness of R&D investment, advertising expenditure and export operations (Nath et al., 2010; Yu et al., 2018). As argued by Mu (2017) and Leung and Sharma (2021), firms’ ability to harmonize their existing resources is likely to reshape their competitive landscape and enable them to achieve “above-average” performance. Hence, capabilities can be viewed as a valuable differentiator that segments firms into above-average (high) and below-average (low) performers, with a substantial effect on the interplay pattern of R&D, advertising and exports.

Currently, little is known about the convolution of relative capabilities with joint strategic factors (i.e. R&D, advertising and exports) in affecting shareholder value (i.e. Tobin’s Q), partly due to the lack of a sound operationalization scheme. As a collective index of the efficiency of firms with a min (input)-max(output) system (Dutta et al., 2005; Yang et al., 2015), capabilities are denoted as a functional representation of both inputs and outputs. From a methodological perspective, efficiency analysis using an optimization method such as data envelopment analysis (DEA) (Ayabakan et al., 2017; Yu et al., 2018) has been widely used;
However, a lack of predictive power and sensitivity to outliers have been noted as the method’s shortcomings. To address such drawbacks, researchers have recently deployed nonparametric machine learning techniques such as MLP (Kwon et al., 2018, 2022b; Molinos-Senante and Maziotis, 2022). In this pioneering study, we follow Dutta et al.’s (2005) conceptualization of firm capabilities and adopt the approach taken by Kwon et al. (2018, 2022a) in operationalizing capabilities and subsequent segmentations.

2.2 Interplay of advertising intensity and R&D intensity
An important question for managers in mature markets is whether investors will view simultaneous increases in advertising intensity and R&D intensity as complementary (i.e., whether the increases will generate increased shareholder valuations) or whether such joint expenditures will be perceived as substitutes, with the ensuing redundancy resulting in reduced shareholder valuations (Askenazy et al., 2016; Doloreux et al., 2018; Peng et al., 2018). Hughes et al. (2018) note that such joint expenditures could be perceived as wasteful, arguing that efforts to develop new markets for the new products resulting from R&D might distract managers from serving their existing markets. Hughes et al. (2018), by analyzing 1,559 USA manufacturing firms, report higher shareholder value with an increase in R&D when marketing expenditures are low, in contrast to the nonsignificant effect of R&D investment along with a high level of marketing expenditure. Their findings on the conflicting effects of R&D and advertising are consistent with Kaiser et al. (2015), who views the combination of R&D investment in innovative products and subsequent marketing activities as a strategic substitute, especially when firms’ innovation efforts are well known to stakeholders, including customers. Similarly, Srinivasan et al. (2009), in their analysis of a single industry (i.e., German automobiles), further argue that promotional activities about the quality of products may send the wrong message about weakness, thereby raising customers’ concerns about legitimacy, which may in turn have adverse effects on stock returns.

In contrast to the research that suggests that R&D and advertising have conflicting effects, another stream of research has reported that there is a complementary relationship in the joint employment of R&D and advertising (Burciu et al., 2020; Kwon et al., 2022b; Peng et al., 2018). For example, Peng et al. (2018), in their investigation of the synergistic effect of the simultaneous deployment of R&D and advertising, use a sample of 317 firms across 27 industry sectors and find that R&D and advertising have a positive interaction, with a significant interaction effect, thereby further supporting the contention that the proper allocation of joint resources has a positive influence on value creation. More recently, Kwon et al. (2022b) have argued that advertising and R&D are mutually reinforcing, with R&D resulting in innovation-driven value creation and advertising enabling value capture. Specifically, R&D creates value by enhancing operational processes and developing new products, and advertising captures value by creating new demand and aligning customers with products. Kwon et al.’s (2022b) analysis of a sample of 206 USA manufacturers indicates that not only does shareholder value increase with individual increases in R&D and advertising intensity, but that joint increases in R&D and advertising intensity have a synergistic effect on shareholder value (i.e., they generate additional shareholder value beyond that which might be expected from the individual effects of advertising and R&D). Their findings are consistent with those reported by Peng et al. (2018).

Although there is a lack of consensus about the joint effect of R&D and advertising on firm performance, recent studies have tended to argue that there is a positive linkage between R&D and advertising, leading to greater performance and stock returns, especially for large firms operating in the global arena (Lee and Kwon, 2021; Peterson and Jeong, 2010). However, while there has been a plethora of research on individual effects and statistical significance, there is still a lack of studies that explore the synergistic interactions between R&D and...
advertising and their impact patterns. Indeed, the dynamic impact patterns of R&D and advertising have hardly been investigated, and the conditional effects of capabilities are also largely unexplored (Kwon et al., 2022b; Lee and Kwon, 2021; Makrini, 2017). Hence, there remains a research void, thus the need to shift attention to the holistic effect of these decision variables and their differential impact patterns beyond statistical significance (Freixanet et al., 2020).

2.3 Interplay of export intensity and R&D intensity

Simultaneously increasing R&D and export intensity may increase a firm’s capacity to generate product and process innovations. Product innovations may result from R&D expenditures, and such innovations become more likely when a firm engages in export activity because it must adapt its products to the different tastes and preferences of foreign customers. Thus, export intensity not only allows a firm to capture economies of scale from its product innovations, but it also provides the firm with a set of market environments (in which a variety of foreign competitors are active) that propel new product development, which is a manifestation of the LBE argument (Carboni and Medda, 2020; Cassiman and Golovko, 2011; D’Angelo et al., 2020). Product development may take the form of new products or modifications to existing products. R&D expenditures directed toward new products are described as exploratory, while expenditures directed towards product modification are referred to as exploitative (Benner and Tushman, 2003). Furthermore, Loecker (2013) notes that exporters can learn about superior production technologies in foreign markets either through buyer–seller relationships or by analyzing the products of foreign competitors. Thus, the stock of knowledge about foreign producers acquired by the exporter can enhance production process innovations that are facilitated by R&D expenditure; this second manifestation of the LBE argument may improve firm productivity (Aw et al., 2008; Baldwin et al., 2016; Golovko et al., 2022; Grossman and Helpman, 1991; Love and Gannatakis, 2013). These LBE arguments support a “virtuous circle” whereby firms use R&D to develop products that can penetrate export markets and where the resulting sales growth both encourages and funds further R&D expenditures (Guarascio et al., 2016; Ke et al., 2020; Lee and Kwon, 2021). The LBE effects, obtained through export intensity to stimulate and enhance the outputs of R&D expenditures, produce synergies that increase the metrics of business performance (Aw et al., 2008; Golovko et al., 2022; Lee and Kwon, 2021; Neves et al., 2016). For example, in a study of Portuguese-based exporters, Neves et al. (2016) reported that individual increases in R&D and export activity had a positive effect on sales growth, and sales growth was enhanced when both activities increased simultaneously. Similarly, in a study of Taiwanese electronic manufacturers, Aw et al. (2008) reported that increases in R&D expenditures and export activities increased firm profitability. Finally, Lee and Kwon’s (2021) study of USA firms also found that there were synergistic effects of R&D intensity and export intensity on the sustainable growth rate for both high- and low-tech firms, although the authors note that the synergistic effects on return on investment were positive only for high-tech firms. Their findings are analogous to those of Barrios et al. (2003), who assert that the impact of R&D spillovers on exports is greater for firms exporting to developed countries [i.e. European Union (EU) or Organization for Economic Co-operation and Development (OECD)], which are likely to be technology-intensive markets. Likewise, exports to high-income countries characterized by substantial knowledge stocks may provide ample opportunities for learning by exporting, especially for high-tech firms (Love and Gannatakis, 2013). With the notion that there is a prospective interaction between R&D and exports that boosts technological capabilities, this study scrutinizes the dynamic interplay of R&D and exports at varying levels of firm capabilities as a meta-resource. It also examines their differential effects on shareholder valuation, which distinguishes this study from earlier efforts.
2.4 Interplay of export intensity and advertising intensity

The export-performance literature has highlighted cost efficiency and marketing differentiation (Kaleka and Morgan, 2019; Aw and Lee, 2017; Yarbrough et al., 2011) as alternative strategies for export growth. A cost-efficiency strategy has the objective of attaining a lower cost for goods sold relative to one’s competition, which enables a brand to compete on price, whereas a marketing differentiation strategy aims to convince customers that a brand has a unique characteristic or set of characteristics that translate into a benefit or benefits not shared by its competitors (Kaleka and Morgan, 2019). An important question is whether advertising campaigns should directly support such export strategies or instead support different marketing objectives. Binet and Field (2007) examined hundreds of advertising campaigns that delivered strong business results on sales, market share and profits. Although many advertising campaigns opted for a persuasive approach consistent with a marketing differentiation or cost-efficiency strategy (i.e. the firms attempted to persuade viewers that their brands had a particular product characteristic or were sold at a price that gave them an advantage over their competition), Binet and Field’s (2007) results indicate that campaigns that adopted the persuasive approach were less effective than advertising approaches that either attempted to build an emotional connection to the brand (emotional approach) or tried to get the ad and brand talked about—a fame approach, with the later approach generating the strongest business results. Similarly, recent research emphasizes that advertising, which enhances a brand’s relative mental availability across a variety of motivations for purchasing a product category, is a key driver of a brand’s market share (Sharp, 2010; Romaniuk and Sharp, 2022). Accordingly, investors may evaluate advertising expenditures directed at export markets on the basis of the relative challenges of building mental availability for brands that are posed by each export market. In the following section, we contend that the challenge of building mental availability will be contingent on whether the firm is attempting to penetrate an existing export market more deeply or attempting to enter new export markets.

Kafouros et al. (2018) distinguish between export breadth and depth. Export breadth increases when export sales increase as a result of increased geographical scope, whereas export depth increases when export sales increase as a result of selling more within existing export markets. An export breadth strategy may require new (and costly) advertising campaigns for different markets, as advertising strategies are developed for markets with different competitors, different media landscapes, different business and legal environments and different category entry points (CEPs) for consumers. CEPs refer to the mental retrieval cues that consumers use to access purchase options (Romaniuk and Sharp, 2022). These CEPs represent differences in a consumer’s desired and actual state. For example, with regard to coffee, CEPs may include the need to alleviate feeling cold, fatigued, or thirsty; the need for an accompaniment in a social meeting with a friend; or the need to concentrate. Successful brands are triggered by CEPs more frequently than their less successful counterparts (Romaniuk and Sharp, 2022). Thus, broad and salient brand associations with CEPs increase both market penetration and market share (Dawes, 2020). Accordingly, an export breadth strategy will require a range of advertising campaigns to respond to the variation in the number and importance of CEPs across export markets. In contrast, an export depth strategy requires a less extensive CEP strategy and may simply require adding to the media spend to obtain an increased share-of-voice for a brand in an existing market (Binet and Field, 2009; Binet and Field, 2018; Cheong et al., 2021), with share-of-voice defined as the proportion of industry advertising spent by the brand in comparison with the advertising expenditure by all brands in the industry (Binet and Field, 2009).

When the opportunities to enter new export markets become saturated, export intensity may increase only by increasing export depth. Investors may see increases in advertising intensity as necessary for USA manufacturers to successfully execute an export breadth strategy; however, they may question the need for an increase in advertising intensity when export intensity is
increasing as a result of an export depth strategy. The reason for investors to be skeptical of advertising intensity increasing when an export depth intensity strategy is being pursued by a USA manufacturer is that an export depth strategy should entail little in the way of additional advertising production costs, but result in media buying efficiencies. For example, World Advertising Research Center (WARC) data indicate that in both Canada and Europe (the two largest export markets for USA manufacturers), the cost per thousand (CPM – i.e. the cost of reaching a thousand viewers) of television advertising is substantially lower than in the USA. Accordingly, investors perceive joint increases in export intensity and advertising intensity as resulting in synergistic effects on shareholder value, which may be contingent on the relative mix of the breadth and depth components of the export intensity strategy. Increases in advertising expenditure to support export intensity driven by a breadth strategy may be looked upon more favorably by investors than when the focus of export intensity shifts to export depth.

In the context of international marketing, advertising is expected to facilitate firms’ entry into overseas markets, especially when firms are short of intangible resources and are new to international operations. As argued by Hultman et al. (2023), investment in advertising is a means to effectively increase brand awareness and enhance familiarity with products in overseas markets, thereby mitigating the “liability of outsidership” (Aluko et al., 2022; Muzychenko and Liesch, 2015). As a cost-effective intangible resource, advertising reinforces the marketing orientation of firms, which is expected to enhance their export operations (Boso et al., 2012; Cavusgil and Knight, 2015). However, there are relatively few studies on the complementary effect of marketing and exports; thus, knowledge about the varying contingencies and diverse empirical settings remains inconclusive (Makrini, 2017; Singh, 2009). For example, Makrini (2017) reports that advertising is negatively related to exports, in contrast to its positive interaction with R&D investment, which further hints at the nonuniform interaction patterns of advertising and exports.

Overall, the interaction mechanisms of joint factors (i.e. R&D, advertising and exports) are expected to be complex and nonlinear, with mutual causality beyond the traditional views of the linkage being linear (Chiva et al., 2014; Sprong et al., 2021; Wu et al., 2021). From a complex system perspective, a simultaneous deployment of multiple factors may generate dynamic interactions, which usher in new interplay patterns (Freixanet et al., 2020; McGregor, 2012). Within a complex paradigm of innovation, marketing and internationalization, three related factors (i.e. R&D, advertising and exports) are viewed as helping firms attain a competitive advantage with emergent impact patterns, which are rarely captured by a linear averaging model (Freixanet et al., 2020; Gupta and Chauhan, 2021). By focusing on the nonlinear interplay of joint factors, researchers have often tried to discern the joint effect within a framework of substituting or complementing, with the former representing a trade-off (or canceling) effect and the latter indicating reinforcing (or synergizing) the relationship upon simultaneous employment of R&D, advertising and exports (Bigos and Michalik, 2020; Burciu et al., 2020; Mitrega et al., 2021; Lee and Kwon, 2021; Randrianasolo and Semenov, 2022; Zhang and Xie, 2020). Most of these studies, however, were devoted to investigating a formatted curvilinear effect rather than the dynamic impact patterns at varying levels of capabilities. Hence, this study uniquely explores the dynamic interplay of R&D, advertising and exports in affecting firm performance by using neural network, an intelligent analytic model, as discussed in the following section.

3. Methods
3.1 Multilayer perceptron (MLP) as a predictive model
Artificial neural networks (ANN), inspired by biological neural networks and the brain’s cognitive system, are commonly characterized by adaptive learning and nonlinear functional approximations, which makes ANN a suitable choice for practical business applications in the
areas of prediction, classification and clustering (Faezy and Hooman, 2017; Kazem, 2023; Rezaei et al., 2019; Wanke et al., 2016; Wei et al., 2022). The multilayer perceptron (MLP) neural network is among the most popular of the supervised learning models, with its strength in abstract learning from limited information and its nonlinear approximation of the production function of multiple input-output variables (Agarwal, 2016; Lee and Kwon, 2021; Wanke et al., 2016). Moreover, unlike parametric statistical models, the MLP is free of a priori assumptions about the distributions of the data set, and hence, it excels in learning arbitrary nonlinear functions of input-output variables and extracting underlying patterns as a format-free data-mining tool (Agarwal, 2016; Molinos-Senante and Maziotis, 2022). The MLP is comprised of a hierarchical array of neurons in distinctive layers (i.e. input, hidden and output) with connections (a.k.a. weights) among neurons in the adjacent layers for iterative information feedforward and error backpropagation during the training (or learning) stages. Upon completion of network training, the MLP model becomes capable of predicting potential outcomes when presented with unknown or new inputs (Lee and Kwon, 2021). Figure 1 depicts a typical three-layer MLP model with incremental neurons in the hidden layer. As illustrated in the figure, the MLP model receives a pair of input and output data sets at the initiation of the training, and the input signals are fanned into the next layers, which is called the feedforward process. The net output is compared to the target output for error calculations. Then, the error is back propagated to the hidden and input layers in sequence, adjusting the relevant weights ($W_h$ and $W_o$). In short, the MLP training involves a repetitive process of information feedforward and error backpropagation until the network reaches the end condition.

As shown in the figure, denoting $X$ as an input vector, the output ($Y$) of the network can be derived from sequential inner products – the inner product of input ($X$) and first weight vector ($W_h$) – to calculate hidden outputs ($H$), which are multiplied by the second weight vector ($W_o$) to determine the final output. With $E$ denoting error in the output layer with $k$ neurons, the feedforward process and error calculation can be expressed in the following arithmetic forms (Kwon et al., 2022b; Lee and Kwon, 2021):

$$Y = f_o(W_o f_h(W_h X))$$  \hspace{1cm} (1)

$$E = \frac{1}{2} \sum (T_k - Y_k)^2,$$  \hspace{1cm} (2)

**Source(s):** Adapted from Kwon et al. (2022b)
where \( f() \) denotes the nonlinear activation function for each layer, which determines the relationships between the neural inputs and outputs. As represented in Eq. (3), the sigmoid functions are commonly used.

\[
f_{v,w}(x) = \left[ 1 + \exp^{-x} \right]^{-1}
\]

During the backpropagation stage, connection weights are updated with a fractional decaying rate, \( \eta(t) \), as expressed in Eq. (4):

\[
W_{o,h}(t+1) = W_{o,h}(t) - \eta(t) \frac{\partial E}{\partial W_{o,j}(t)}
\]

After training the model, the final information stored on the weights interconnecting the neurons functions as a key code to be applied to incoming signals, such as unknown inputs. Due to its nonlinear processing and adaptive learning capabilities, the MLP model has unique strengths in fine-precision predictions. The invisible nature of the processing mechanism of the MLP with embedded hidden neurons makes the interpretation of internal processing a cumbersome task. However, the sensitivity analysis scheme (Kowalski and Kusy, 2018; Lee and Kwon, 2021; Naeimi et al., 2015; Wanke et al., 2016) is a valuable mechanism for measuring the impact scale of each input and allows for further detection of the synergistic effect as proposed in this study. Moreover, as a curve-fitting model, the MLP forms a nonlinear decision surface, which segments firms into two performance categories, above-average and below-average, representing high and low capabilities (Agarwal, 2016; Kwon et al., 2018; Molinos-Senante and Maziotis, 2022; Santín et al., 2004). The unique advantage of the MLP in the nonlinear segmentation of firms and synergy analytics has provided a meaningful technical basis for this study. By exploring the predictive potential of the MLP as a primary empirical model, we present a complementary MRA-MLP approach.

### 3.2 Analytic process design

The proposed empirical framework comprises a four-phase sequential process designed for (1) determining the general effect of key factors: R&D, advertising and exports; (2) measuring the relative importance of each factor and (3) extracting the differential impact of joint variables contingent on capabilities, both high and low. The overall process incorporates two complementary techniques: parametric MRA and nonparametric MLP neural network, alias back-propagation neural network (BPNN), as illustrated in Figure 2.

![Figure 2. The analytic scheme and empirical design](image)

**Note(s):** MRA-Multiple Regression Analysis  
MLP-Multilayer Perceptron Neural Network  
**Source(s):** Authors’ own work
As a preliminary step, MRA determines the statistical significance of independent variables, providing general insights into the relationships between key variables with respect to performance (step 1). Then, building on the same data set, the first MLP model learns nonlinear functions on input–output relationships for an exploration of the relative impact of inputs (step 2). Although information processing in the MLP is not explicitly observable, the sensitivity analysis scheme (Kowalski and Kusy, 2018; Lee and Kwon, 2021) enables the detection of output variation as a system response to an input stimulus, which enhances the potential utility of the MLP for an explanatory analysis that complements traditional approaches (Naeimi et al., 2015; Wanke et al., 2016). As such, the first phase of analysis (Step 1 and Step 2) is centered on explanatory analysis in general, with a particular interest in exploring the centralized impact patterns of individual inputs.

The first phase of analysis is a centralized model approach in that the analytic scheme is designed to extract the average trend or general functional relationships of input and output variables. Such a mixed-sample approach, however, is less likely to uncover the distinctive characteristics and differentiable patterns embedded in the experimental data. That is, the whole sample approach may result in too much generalization, thereby oversimplifying potentially complex production functions that may be affected by contingent factors, such as capabilities in the present study. With particular attention to capabilities, the second phase of analysis is directed toward capturing the differential impact patterns through segmentation modeling. In this empirical advancement, the first MLP model in Step 2 provides a hint at how to segment entire data sets into two distinctive subsets according to the level of capability (high or low). Unlike common segmentations based on contextual contingency (e.g. firm size, exports and industry), capability-based categorization requires a well-defined decision surface formulated through a reliable production function. The residuals (+/-) of the MLP predictions were adopted as a surrogate representation of relative capabilities, with the sign indicating high (+) and low (-) capabilities, respectively (Kwon et al., 2018; Molinos-Senante and Maziotis, 2022; Santín et al., 2004).

Next, two subsequent MLP models (step 3) in phase 2 are tasked with learning differential impact patterns for each category (high and low). In so doing, the second phase of analysis is designed to detect distinctive but contrasting impact patterns for each segment of capabilities. From a modeling perspective, the segmentation approach enhances the monotonicity of the subset, which reduces fluctuation in the model and helps to ensure stable learning (Pendharkar and Rodger, 2003). Hence, the curve-fitting property of the MLP (which bisects the entire data set into two segments) is at the core of this innovative modeling approach. In the second phase of analysis, two subsequent MLP models detect contrasting interaction effects and the synergistic rents for each capability level, with particular attention to the dynamic interplay of R&D, advertising and exports with respect to shareholder value.

3.3 Data and variables
3.3.1 Sample data collection. The sample data used for this study include 206 USA manufacturing firms selected from the S&P Capital IQ database, excluding any items that are missing data for the variables of interest in this study. After extracting the data set from the database, we first eliminated the data from financial institutions (SIC 6000–6999) and nonmanufacturing firms so that we could focus on manufacturing firms in the USA. Hence, the data set used for this study covers firms with SICs ranging from 2,000 to 3,900, which encompasses both low- and high-tech firms. In addition, we excluded firms with less than $US100m in revenue and those that did not include information about their advertising expenditures, R&D expenditures and export volumes. Then, to ensure the study’s integrity, firms with missing or nonreporting data for selected variables (i.e. firm size, capital, inventory, current ratio and Tobin’s Q) were also eliminated. After screening, 206 manufacturing firms,
including 85 low-tech firms and 121 high-tech firms, were used, as summarized in Table 4, along with the segmentation results by the MLP for each industry. To help ensure reliable predictive outcomes, we used five-year aggregated averages (2013–2017) of all factors to avoid year-to-year floating effects and to minimize the effect of an irregular occurrence of data (Hall and Lee, 2014; Kwon et al., 2022a).

3.3.2 Selection of variables. The data set collected for this study includes eight variables, with particular attention to three key input factors (i.e. advertising, R&D and exports) in conjunction with four other control variables, which include firm size, capital intensity, current ratio and inventory turnover. Firm size is one of the most acknowledged determinants of a firm’s performance in terms of its effects on competitive market power via R&D, advertising and exporting (Feng et al., 2017; Jacobs et al., 2016; Mu, 2017). Large firms accrue economic benefits as a result of their ability to exercise financial leverage, economies of scale and operational cost efficiency (Golovko et al., 2022; Peng et al., 2018; Zhou et al., 2023). Accordingly, large firms have an advantage in global operations because of their competitive growth potential and profitability, and they are expected to generate greater synergistic interactions between R&D and advertising than small-sized enterprises (Tyagi and Nauriyal, 2017; Peng et al., 2018). Capital intensity has been validated as a major control factor in affecting the export performance and competitive advantage of manufacturing firms through their commitment of operational resources and the quality of their products (Golovko et al., 2022; Hansson and Lundin, 2004). Capital investment allows firms to gain additional capacity for new product development and technical progress, thereby affecting their ability to achieve a competitive advantage in international markets (Neves et al., 2016; Lee and Kwon, 2021; Zhou, 2021). In general, capital-intensive firms have greater potential to renovate their production processes and initiate product innovation, thereby enhancing their competitive edge amid intense competition (Adetunji and Owolabi, 2016; Lee et al., 2019). The current ratio is one of a firm’s most useful liquidity measures for insulating it from its short-term financial obligations and projecting its financial health under uncertain economic conditions. Although there is some disagreement over the effect of the current ratio (Borhan et al., 2014; Jaworski and Czerwonka, 2022; Muhammad et al., 2014), firms with a higher current ratio are good at utilizing resources and sustaining supplier relationships when launching new product development and embarking on a market expansion, which affects their economic performance and market valuation (Bibi and Amjad, 2017; David et al., 2015; Kariv et al., 2017). Inventory turnover is used as one of the key operational factors and performance measures in manufacturing industries because it affects cash generation and the efficient utilization of financial assets, especially when firms are committed to developing innovative products and competing in the global market (Kwak, 2019; Pati and Lee, 2023; Shardeo, 2015). As a surrogate measure of lean operations, inventory turnover allows the firm to maintain sound asset capacity for better financial performance, which is linked to important decision areas across purchasing, production, marketing and exports (Ahmad and Mahmood, 2018; Boute et al., 2007; Demeter and Matyusz, 2011; Khan et al., 2016; Vidhyapryla et al., 2020). However, even among manufacturers, inventory turnover is likely to be significantly different depending on contingent factors such as industry sector and product type (Demeter and Matyusz, 2011). As such, along with selected control factors, this study explores the dynamic interplay of key inputs (i.e. advertising, R&D and exports) and their impacts on Tobin’s Q as a forward-looking market performance, which is commonly adopted as a performance measure for manufacturing firms (Agarwal, 2016; Jacobs et al., 2016; Pati and Lee, 2023). In this study, the operationalization of all strategic factors can be summarized as follows:

(1) Firm size (FS) = Natural log (total sales);

(2) Capital intensity (CP) = Invested capital/Total sales;
Table 1 summarizes the descriptive statistics for the eight variables used for this analysis and displays the correlation coefficients among interrelated variables, as well as the significance levels. Notably, the relationship between Tobin's Q and the three key factors (advertising, R&D and exports) are positive and significant at least at the 0.01 level, with the highest correlation coefficient being R&D (0.468), followed by exports (0.455) and advertising (0.172). These input factors exhibit common significant relationships with the current ratio, further showing positive (R&D and exports) and negative (advertising) correlations. Tobin's Q also shows a positively significant relationship with only the current ratio out of four other control variables. In addition, no significant intercorrelations exist among advertising, R&D and exports.

4. Results
4.1 Explanatory effect analysis using MRA
As a first step toward sequential neural network modeling, MRA was conducted to discern the relationship of each factor with the output and its statistical significance as a linear averaging format when using the entire data set. The model output is expected to present overall insights in terms of individual effects in a general sense as a basis for the sequential prediction experiments. Table 2 summarizes the experimental results of the regression analysis (Step 1).

The result shows a statistically significant (<0.001) model output with no hints of multicollinearity between inputs, as evidenced by small variance inflation factors (VIFs) (<10), as summarized in Table 2. All variables except for inventory (IV) are determined to be significant at least at the 0.05 level. In addition, the significant variables except for capital intensity show a positive relationship with Tobin’s Q. More importantly, all three key factors of interest are significant, with advertising being significant at the 0.05 level, in contrast to the greater significance level (<0.001) of R&D and exports. Overall, the MRA result conveys meaningful information that the three resources (i.e. R&D, advertising and exports) play a significant role in increasing shareholder value in the USA manufacturing sector in particular. The result further triggers empirical progression as to assessing the relative impact scale on shareholder value, especially with the combinatory coordination of joint resources, which is not observed from the MRA. Moreover, the incorporation of capabilities into an analytic frame adds complexity, necessitating a sophisticated prediction mechanism to cope with asymmetric input-output dynamism.

4.2 Progressive network design and capability segmentation using MLP
4.2.1 Two-stage sequential model design. Complementing the statistical regression analysis, neural network-based predictive modeling was conducted for further exploration of the relative impact of the key factors (R&D, advertising and exports), along with the control Interplay of R&D, advertising and exports
<table>
<thead>
<tr>
<th>Var</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Firm size</td>
<td>7.835</td>
<td>1.427</td>
<td>4.496</td>
<td>12.016</td>
<td>0.173*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Capital</td>
<td>1.241</td>
<td>0.637</td>
<td>0.349</td>
<td>3.661</td>
<td>0.173*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Current ratio</td>
<td>2.755</td>
<td>1.673</td>
<td>0.681</td>
<td>12.359</td>
<td>-0.398**</td>
<td>0.175*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Inventory</td>
<td>5.882</td>
<td>6.590</td>
<td>0.763</td>
<td>73.335</td>
<td>0.267**</td>
<td>-0.073</td>
<td>-0.218***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Advertising</td>
<td>0.291</td>
<td>0.041</td>
<td>0.000</td>
<td>0.266</td>
<td>0.115</td>
<td>-0.057</td>
<td>-0.182**</td>
<td>-0.081</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. R&amp;D</td>
<td>0.045</td>
<td>0.081</td>
<td>0.000</td>
<td>0.498</td>
<td>-0.387**</td>
<td>0.036</td>
<td>0.326**</td>
<td>-0.044</td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Exports</td>
<td>0.439</td>
<td>0.266</td>
<td>0.001</td>
<td>0.988</td>
<td>0.162*</td>
<td>0.085</td>
<td>0.154*</td>
<td>-0.064</td>
<td>0.085</td>
<td>0.123</td>
<td></td>
</tr>
<tr>
<td>8. Tobin’s Q</td>
<td>2.061</td>
<td>1.242</td>
<td>0.525</td>
<td>7.973</td>
<td>0.044</td>
<td>-0.060</td>
<td>0.218***</td>
<td>-0.026</td>
<td>0.172*</td>
<td>0.468**</td>
<td>0.455**</td>
</tr>
</tbody>
</table>

**Source(s):** Authors' own work
factors, before proceeding to the differential segmentation analysis. The neural network model approximates underlying input-output production functions, which allows prediction on unseen data sets. For neural network modeling, as part of a generalized learning scheme, the data set was partitioned into three subsets (training, test and validation). In this hold-out sample approach, the validation subset was used to verify the effectiveness of the trained model for generalization purposes. For the first MLP model, the entire data set was partitioned into training (132), test (44) and validation (30) subsets. By using the incremental learning approach, where hidden neurons are added as needed, the final model resulted in a 7-9-1 structure representing seven input neurons, nine hidden neurons and one output neuron. [Note: The training result of the model is summarized in Table 3 alongside the results from two sequential models (step 3) for comparative purposes]. As summarized in the table, the MLP model separates the total samples into two segments (92 and 114), and two subsequent MLP models were implemented by applying the same data partitioning scheme. Across all three models, two performance measures were used, which included Pearson R to represent correlations between actual and predicted outcomes and mean absolute percentage

<table>
<thead>
<tr>
<th>Variables</th>
<th>Unstandardized β (Std. ε)</th>
<th>Stand. β</th>
<th>t-value</th>
<th>Sig. Level</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td>-0.742 (0.477)</td>
<td>-1.544</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm size (FS)</td>
<td>0.228 (0.059)</td>
<td>0.262</td>
<td>3.899</td>
<td>***</td>
<td>1.649</td>
</tr>
<tr>
<td>Capital intensity (CP)</td>
<td>-0.338 (0.109)</td>
<td>-0.173</td>
<td>-3.105</td>
<td>**</td>
<td>1.134</td>
</tr>
<tr>
<td>Current ratio (CR)</td>
<td>0.122 (0.047)</td>
<td>0.165</td>
<td>2.619</td>
<td>**</td>
<td>1.141</td>
</tr>
<tr>
<td>Inventory turnover (IV)</td>
<td>-0.004 (0.011)</td>
<td>-0.019</td>
<td>-0.345</td>
<td></td>
<td>1.153</td>
</tr>
<tr>
<td>Advertising intensity (AD)</td>
<td>3.974 (1.649)</td>
<td>0.131</td>
<td>2.410</td>
<td>*</td>
<td>1.078</td>
</tr>
<tr>
<td>R&amp;D intensity (RD)</td>
<td>7.342 (0.910)</td>
<td>0.481</td>
<td>8.069</td>
<td>***</td>
<td>1.293</td>
</tr>
<tr>
<td>Exports (EX)</td>
<td>1.541 (0.261)</td>
<td>0.330</td>
<td>5.893</td>
<td>***</td>
<td>1.141</td>
</tr>
</tbody>
</table>

Note(s): \( R^2 = 0.456; \) Adj. \( R^2 = 0.437; \) \( F \)-ratio = 23.720***
VIF indicates variance inflationary factor to detect the multicollinearity problem
*\( p < 0.05, **p < 0.01 \) and ***\( p < 0.001 \)

Source(s): Authors’ own work

Table 2. Results of multiple regression analysis (MRA)

Interplay of R&D, advertising and exports

<table>
<thead>
<tr>
<th>Model</th>
<th>MLP(^1)</th>
<th>MLP(^2)</th>
<th>MLP(^3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data sample</td>
<td>Total: 206</td>
<td>Total: 92</td>
<td>Total: 114</td>
</tr>
<tr>
<td>Train: 132</td>
<td>Train: 59</td>
<td>Train: 72</td>
<td></td>
</tr>
<tr>
<td>Test: 44</td>
<td>Test: 20</td>
<td>Test: 25</td>
<td></td>
</tr>
<tr>
<td>Valid: 30</td>
<td>Valid: 13</td>
<td>Valid: 17</td>
<td></td>
</tr>
<tr>
<td>Network structure</td>
<td>7-9-1</td>
<td>7-7-1</td>
<td>7-10-1</td>
</tr>
<tr>
<td>Input: 7</td>
<td>Input: 7</td>
<td>Input: 7</td>
<td></td>
</tr>
<tr>
<td>Hidden: 9</td>
<td>Hidden: 7</td>
<td>Hidden: 10</td>
<td></td>
</tr>
<tr>
<td>Output: 1</td>
<td>Output: 1</td>
<td>Output: 1</td>
<td></td>
</tr>
<tr>
<td>(^4)Pearson R</td>
<td>All: 0.783</td>
<td>All: 0.880</td>
<td>All: 0.932</td>
</tr>
<tr>
<td>Train: 0.780</td>
<td>Train: 0.884</td>
<td>Train: 0.947</td>
<td></td>
</tr>
<tr>
<td>Test: 0.730</td>
<td>Test: 0.874</td>
<td>Test: 0.933</td>
<td></td>
</tr>
<tr>
<td>Valid: 0.840</td>
<td>Valid: 0.882</td>
<td>Valid: 0.915</td>
<td></td>
</tr>
<tr>
<td>(^5)MAPE (Median)</td>
<td>35.3% (25.5%)</td>
<td>17.9% (16.6%)</td>
<td>20.5% (16.0%)</td>
</tr>
</tbody>
</table>

Note(s): \(^1\)All data, \(^2\)High capabilities (subset) and \(^3\)Low capabilities (subset)\n\(^4\)Pearson R: Correlation between target and prediction output\n\(^5\)MAPE: Mean absolute percentage error

Source(s): Authors’ own work

Table 3. Summary of neural network training
error (MAPE) to address the scale of prediction errors. The Pearson R in each model shows similar levels of correlation across the three partitioned subsets, including a validation subset, which suggests that there are no potential concerns about the overfitting of models, thus implying successful generalized learning of the models for prediction tasks.

4.2.2 Capability segmentation. The MLP model in the first phase plays an important role in that it establishes a nonlinear decision surface, which allows for capability-based segmentation. Simply put, firms above the decision surface can be treated as above-average performers and categorized as a segment of high capabilities, with the other side categorized as a below-average or low-capability segment in a relative sense (Kwon et al., 2018). Hence, two subsequent MLP models are expected to demonstrate less fluctuation in prediction modeling due to the enhanced monotonicity of the subsets (high and low), and the result in Table 3 shows higher correlations and smaller MAPEs from the segmented models. Figure 3 contrasts residuals in terms of absolute percentage error from three MLP models, thereby highlighting the span of residuals from the two segmented models (high and low) within the range of the first MLP model built on the entire data set.

Besides the reduced error scale from the segmented models, Figure 3 also hints at efficiency-based capability measures. In fact, in addition to the two-group segmentation (+ residuals), the relative scale of residuals can serve as a proxy for a surrogate capability measure (Kwon et al., 2018; Molinos-Senante and Maziotis, 2022; Pendharkar, 2011; Santín et al., 2004). Adopting Kwon et al. (2018), the efficiency-based relative capability of a company (J) can be represented by the ratio of actual ($y_{a,J}$)/prediction ($y_{nn,J}$) values and depending on the applications, the value may be further normalized with the following general notation: 

$$\frac{[y_{a,J}/y_{nn,J}]}{\text{Max} \{y_{a,J}/y_{nn,J}\}}.$$  

In this efficiency-based capability measure, the first MLP model determined the range of capabilities (0.320 through 4.240) with an average capability of 1.018. The MLP model, as specified in Table 3, segmented firms into high (92) and low (114) classes with a noticeable difference (<0.001) of mean value only in Tobin’s Q (2.798, 1.466), with comparable means on input variables such as firm size (7.813, 7.852), capital (1.312, 1.184), current ratio (2.862, 2.669), inventory (6.441, 5.440), advertising (0.030, 0.028), R&D (0.048, 0.041) and exports (0.459, 0.422). The segmentation result shows that capabilities make a difference in shareholder valuation, with higher capabilities resulting in greater shareholder value even for comparable levels of resource allocations. Table 4 displays the data sets briefly explained in the earlier section (3.2), along with the segmentation outcomes for respective industry classes. Aside from industry-wise classifications, the MLP result reveals the interesting finding that high-capability firms are more composed of high-tech firms and that low-tech firms are more susceptible to having low capabilities.

![Figure 3. Illustration of two-stage segmentation modeling](source)

**Source(s):** Authors’ own work
4.3 Differential impact and synergistic effect analysis

4.3.1 Relative importance and differential impact. For predictive MLP modeling, three sequential analyses were conducted to measure the relative importance of each input variable. The first experiment was based on the entire data set, with two subsequent predictions to detect the contrasting impact scales according to the varying capabilities. Figure 4 shows the relative impact of each variable at varying capabilities, with reference to the impact of the average model built on the entire set of data. The overall impact from all data shows the biggest impact from firm size (FS), followed by exports (EX), R&D (RD) and advertising (AD) and current ratio (CR), with a negative impact for capital (CP) and inventory (IV) and the negative impact also being observed in both segmented models. It is noteworthy that the segmentation approach further reveals comparable impact patterns according to the different capabilities, a result that would not be exposed in the mixed-sample model. The figure shows that firm size has the biggest impact for high-capability firms, but for low-capability firms, the impact of the CR appears to be the greatest. More importantly, all three models report positive impacts from the key variables of interest (advertising, R&D and

![Figure 4](image)

**Source(s):** Authors’ own work
exports) but with varying scales. For high-capability firms, the impact scales are, in order, exports, R&D and advertising, which is in line with the mixed-model result, but for low-capability firms, advertising has a bigger impact than R&D, after exports. In addition to relative importance, the marginal effect of the three key factors (advertising, R&D and exports), as represented by the actual impact scale, further exposes the vivid distinctions between the two segments (high and low) of capabilities. As highlighted in Figure 4, exports appear to be the most impactful factor for both categories, but with a large discrepancy, with 0.0082 for high-capability firms and 0.0013 for low-capability firms, accounting for 16% of high-capability firms. The actual impact of R&D is the second-largest in high-capability firms (0.0032), which is far greater than the effect in low-capability firms (0.0003). The effect of advertising is slightly bigger in low-capability firms, and for the low category, the effect of advertising (0.001) far exceeds the effect of R&D (0.0003), which accounts for a 30% level of advertising. These figures exist in vivid contrast to the case of high-capability firms, which shows a greater effect of R&D (0.0032), as compared to the smaller effect of advertising (0.0008), indicating a 25% scale of R&D. Simply put, R&D matters more than advertising for high-capability firms in comparison to the adverse effect in low-capability firms. In brief, the relative impact of exports, R&D and advertising, along with the differential effect at varying capability levels, provides a rational motivation for further scrutiny of synergistic interactions when resources are deployed simultaneously.

4.3.2 Contingent synergy effect. The interactions of two joint variables were commonly explained by a complementarity or substitute relationship, with the former arguing for positive reinforcement due to an additive effect and the latter a deductive effect due to the redundant or trade-off nature of joint resources. Earlier studies (Peng et al., 2018; Zhang and Xie, 2020) commonly relied on statistical techniques to investigate the nonlinear interactions of joint variables; however, the result was often confined to a formatted frame of curvilinearity (Fujii et al., 2013; Trumpp and Guenther, 2017). It should be noted that these attempts are prone to oversimplifying the underlying complexity, thereby lacking a predictive mechanism for capturing potentially nonsymmetric impact patterns. Hence, the exploration of complex impact patterns demands a methodological sophistication capable of adaptive learning and intelligent processing without a priori assumptions. There have been rare attempts to address this methodological concern (Makrini, 2017); however, recent advancements using neural networks provide a sound basis for further exploration of the joint effects. As proposed by recent studies (Kwon et al., 2022b; Lee and Kwon, 2021), the scalar representation of the synergistic impact of joint factors can be briefly expressed in a functional representation: \( F_{\text{syn}} (J & K) = \{ f_{\text{nn}}(x_J^+, x_K^+, x_i) - [f_{\text{nn}}(x_J^+, x_i) + f_{\text{nn}}(x_K^+, x_i)] \} \), where functional notation \( f_{\text{nn}}(x_J^+, x_i) \) represents neural network prediction as a marginal response to a unit increase of a particular input \( (x_j) \), with other inputs \( (x_i) \) remaining constant. Accordingly, the discrepancy between a joint effect upon simultaneous increases of interested factors \( (J \text{ and } K) \) and the sum of two individual effects is an indication of the synergistic effect. In this study, two MLP models conducted synergy analytics for three pairs of joint factors (i.e. AD & RD, RD & EX and AD & EX) under varying capabilities through iterative predictions for incremental inputs up to 10%. Table 5 summarizes procedural flows and relevant prediction outcomes for synergy analytics, and Figure 5 presents a graphical summary of the resulting impact patterns and trajectories.

As illustrated in Figure 5, the synergistic patterns differ across pairs of joint factors, with a noteworthy contrast between two capability segments (high and low). First, the synergy patterns of advertising and R&D reveal a vivid contrast between firms at different levels of capability. For high-capability firms, the joint increase in advertising and R&D (AD & RD) generates additional effects, thereby implying a mutually reinforcing relationship. For these firms, marketing investment appears to enhance awareness of new products and quality features. For low-capability firms, in contrast, the joint emphasis of advertising and R&D
## Results of Predictive Synergy Analysis

### Interplay of R&D, Advertising, and Exports

<table>
<thead>
<tr>
<th>Data</th>
<th>Predictive analysis</th>
<th>Incremental input</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1%</td>
</tr>
<tr>
<td><strong>High-capability firms</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(f_{an} (AD^+)^{1} )</td>
<td>2.880</td>
<td>2.881</td>
</tr>
<tr>
<td>(f_{an} (RD^+)^{1} )</td>
<td>2.883</td>
<td>2.886</td>
</tr>
<tr>
<td>(f_{an} (EX^+)^{1} )</td>
<td>2.888</td>
<td>2.895</td>
</tr>
<tr>
<td>(f_{an} (AD^+ &amp; RD^+)^{1} )</td>
<td>2.883</td>
<td>2.887</td>
</tr>
<tr>
<td>(f_{an} (RD^+ &amp; EX^+)^{1} )</td>
<td>2.891</td>
<td>2.902</td>
</tr>
<tr>
<td>(f_{an} (AD^+ &amp; EX^+)^{1} )</td>
<td>2.888</td>
<td>2.897</td>
</tr>
<tr>
<td>(F_{syn} (AD &amp; RD)^{1} )</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>(F_{syn} (RD &amp; EX)^{1} )</td>
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Source(s): Authors' own work
(AD & RD) does not generate positive synergy; rather, it causes an adverse effect, thereby exhibiting a cancellation effect. Interestingly, apart from synergy patterns, the contrasting effect was also apparent in their relative importance (see Figure 4), with the low-capability segment showing greater returns from advertising than R&D in comparison to a greater R&D effect in high-capability firms. Second, the synergy between R&D and exports (RD & EX) is positive in both capability segments, with greater synergistic rents for high-capability firms. Indeed, high-capability firms exhibit an exponential pattern of synergy increases, in contrast to the smaller scale of incremental effects in low-capability firms. Finally, the interaction between exports and advertising (EX & AD) results in interesting synergy patterns. In contrast to the small and steadily increasing effect from low-capability firms, the
high-capability firms present the inverted U-shape pattern of synergy but with specific impact scales upon the incremental deployment of joint resources. More interestingly, the result reveals an optimal level of combined resources for achieving the maximum level of synergy rent. Specifically, in this setting, the joint increases of exports and advertising (EX & AD) by 4% are expected to yield the highest level of additive effect. Additional investment beyond the tipping point may result in a diminishing effect, with negative returns beyond a certain point (i.e. 6%), thereupon inducing a substitute effect. Taken together, these empirical results present new insights into the interplay of three related resources, especially under differential capabilities.

5. Discussion, implications and concluding remarks
5.1 Discussion
In this empirical study, the level of firm capabilities assumed a crucial role in affecting the comparative importance of key factors (advertising, R&D and exports) and in capturing the differential impact patterns – results that are barely detectable by linear averaging methods. The vivid contrast of impact scales (as presented in Figure 4) is a manifestation of effective segmentation modeling. Aside from the consistently highest impact of exports in both categories, and despite the discrepancy in scale, the reversal of R&D and advertising in their respective impacts on high- and low-capability firms conveys meaningful information. The category of high-capability firms (as classified in Table 4) has more firms in high-tech industries, which compete on product quality in a growing market. Likewise, the product market is expected to respond favorably to the pragmatic attributes of a pristine product instead of ambiguous emotional content (Luo and Bhattacharya, 2006). Also, for shareholders, an increase in R&D by highly capable firms enhances both the quality and innovativeness of products, which helps sustain their market performance. Accordingly, the higher importance of R&D over advertising in high-capability firms is apparent. In contrast, low-capability firms exhibit sub-par proficiency in resource utilization, and their lower status is reflected in their relatively low market valuations. In our sample, a majority of low-tech firms belong to this segment. These low-tech firms compete in less dynamic market environments with mature product life cycles, and there is less emphasis on technological innovation. Alongside these low-tech firms, the high-tech firms in this segment receive a less favorable market reaction to their product offerings and, subsequently, a less prestigious standing. For those firms competing in mature market environments and receiving less favorable valuations, investment in advertising to strengthen relational assets with emotional aspects of the product appears to have a greater effect than what would be obtained by focusing on knowledge assets (Chandy et al., 2001; Dall'Olio and Vakratsas, 2023). For such firms, emphasis on R&D is less likely to appeal to investors as a primary driver of firm valuation. As such, for low-capability firms, the empirical model detected that marketing had a greater influence through investments in advertising than did attempts at technological innovation through R&D investment.

Beyond the relative importance of individual factors, synergy analytics presents additional insights into the dynamic interplay of related factors. First, the contrasting impact patterns of advertising and R&D, contingent on capabilities, are one of this study’s most noteworthy findings. Based on the result, investors seem to view advertising and R&D as complementary for high-capability firms (i.e. firms with high a shareholder valuation). Such firms are more likely to inhabit high-growth markets, where industry product innovation is likely to be more common, and as a result, R&D may be viewed as essential to a firm’s survival since withholding R&D expenditures may increase the probability of a product becoming obsolete. High-growth markets are characterized by an inflow of new consumers who need to be made aware of a brand’s name and availability (Sharp, 2010),
encouraged to attach a positive set of emotions to the brand (Binet and Field, 2009) and informed about any product advantages emanating from R&D expenditures. In contrast, low-capability firms are more likely to occupy lower (or even negative) growth markets. In these mature markets, investors may view high advertising intensity as crucial to increasing (or at least defending) market share via its effects on share-of-voice (Binet and Field, 2018). In contrast to high-growth markets, R&D in mature markets is less likely to generate valuable product innovations, and investors may view high R&D expenditures as a wasteful diversion of resources that may be better spent on increasing advertising share-of-voice (Binet and Field, 2009; Luo and de Jong, 2012). Hence, in contrast to reinforcing the effect in high-capability firms, a substituting effect of advertising and R&D was observed, implying the potential erosion of the effect in low-capability firms.

Second, the synergistic interaction between R&D and exports is positive at both capability levels, but with a greater effect in high-capability firms. If shareholder value is partly driven by domestic market growth opportunities, then it is likely that USA manufacturers with high shareholder value will be more likely to encounter export markets that are also characterized by high growth potential than will be the case for low shareholder-value firms, although it is possible that some low shareholder-value USA manufacturers may find that their export markets are at an earlier stage of development (i.e. they offer higher growth potential than their more mature domestic markets). Accordingly, the product development opportunities that underpin one aspect of the LBE argument are more likely to be available to exporting USA manufacturers with high shareholder value, and so investors may perceive such manufacturers as more likely to reap greater synergistic effects when export intensity and R&D intensity are jointly increased than would be the case for USA manufacturers with low shareholder value. Indeed, the greater impact of high-capability firms manifests in the cooperative role of organizational proficiency in nurturing the reciprocity of R&D and exports from the complementary perspective of knowledge creation and knowledge acquisition (Howell, 2019; Masso and Vahter, 2015; Wilhelm et al., 2015; Wu et al., 2010).

Third, the exploration of advertising and exports reveals a noticeable contrast in their differential impact patterns, adding a unique insight into the interactive behaviors of advertising and exports. The inverted U-shaped pattern of impact for high-capability firms may be indicative of an export breadth strategy reaching saturation with an ensuing greater role for export depth in the export intensity mix, resulting in advertising intensity increases being perceived less favorably by investors. In contrast, the steady synergistic response of advertising intensity and export intensity for low-shareholder-value firms may indicate that investors believe that export breadth has not reached saturation, and so supportive increases in advertising intensity are necessary. In general, high-capability firms are known to retain managerial ability, which facilitates absorptive learning and adaptation capabilities and enables the firm to skillfully navigate complex market situations (Mu, 2017). Indeed, high-capability firms (those retaining greater efficiency and having high shareholder values) are more confident in their capacity to penetrate multiple export markets with a broader scope of products, thereby expanding the span of their knowledge base (Jacobs et al., 2016; Mu, 2017). In this sense, swift and timely adaptation to diverse overseas markets is likely to mitigate the information asymmetry and enhance products’ perceived value, allowing firms to reduce their redundant promotional efforts (Bernard et al., 2011; Golovko et al., 2022; Hultman et al., 2011; Masso and Vahter, 2015). This finding is also consistent with the greatest single impact of exports on firm valuation in this category (as shown in Figure 4), and it signifies the role of capabilities as a core determinant of exports and shareholder valuation, which is in line with the RBV theoretic lens (Dutta et al., 2005; Gupta and Chauhan, 2021; Yang et al., 2015). Overall, in addition to the contingent role of capabilities, the exploration of the complex interplay among advertising, exports and R&D presents new findings and calls for continued attention to this emergent research topic.
5.2 Theoretical implications

This study presents a new avenue of research for exploring complex interactions among three key resources (i.e., advertising, R&D and exports) at varying capability levels. Earlier studies investigated the joint effects of advertising and R&D (Askenazy et al., 2016; Doloreux et al., 2018; Hsiao et al., 2021; Hughes et al., 2018; Kwon et al., 2022b; Peng et al., 2018); R&D and exports (Baldwin et al., 2016; D’Angelo et al., 2020; Sikharulidze and Kikutadze, 2017); and exports and advertising, or marketing in general (Hultman et al., 2011; Jindal, 2020; Lee and Kwon, 2021; Makrini, 2017; Morales et al., 2019; Zhang and Zhu, 2016). Despite diverse views and differing results in various empirical settings, most of these studies were devoted to testing hypothetical statements, with the effects confined within a linear or curvilinear format, with the rare exception of nonparametric approaches (Kwon et al., 2022b; Lee and Kwon, 2021). However, there is still a research void in exploring the holistic pattern of interplay among three pillars of resources – advertising, R&D and exports – which appears particularly contingent on firm capabilities. By proposing a salient analytic process for the segmentation of capabilities and adaptive prediction modeling, this study fills the research gap.

Hence, as explorative research, this study makes several contributions to the extant literature from both the theoretical and managerial perspectives. From a theoretical standpoint, it incorporates capabilities as a contingent factor, which delineates an obscure resource-performance link into differentiable value-formulation channels. From the RBV standpoint, a stock of resources alone is not sufficient for achieving competitive advantages; rather, such resources should be interwoven according to complementary capabilities (Gupta and Chauhan, 2021; Yang et al., 2015; Yu et al., 2018). Despite offering a rich conceptualization of capabilities, empirical scrutiny of the effect size of capabilities has been rare, partly due to the lack of reliable metrics to quantify capabilities (Ayabakan et al., 2017; Ramanathan et al., 2016; Shilke et al., 2018). By circumventing the technical shortfalls in operationalizing capabilities, this study spotlights their intermediary role, uncovering their conditional effect on the resource-performance link. It also highlights the dynamic interplay of resources (i.e., advertising, R&D and exports), which is contingent and complex beyond the uniform and linear relationships. In this sense, this explorative study provides new insights into the value-formulating chain of resources, capabilities and performance in light of the theoretic frame of RBV (Gupta and Chauhan, 2021; Shilke et al., 2018; Teece, 2014).

According to the proponents of the resource-orchestration theory (ROT), RBV has shortcomings in that it does not properly address the varying performance levels of firms upon the deployment of similar resources, and it lacks the capacity to explain how to harmonize the resources for a sustained competitive advantage (Awe et al., 2020; Bhandari et al., 2023; Hughes et al., 2018; Sirmon et al., 2007). Hughes et al. (2018) posit that ROT extends RBV and emphasizes managerial proficiency in deploying resources, further asserting ROT as a prospective frame for scrutinizing the relationship between resources and performance in manufacturing firms. From this perspective, by allowing hypothetical what-if scenarios of joint resources and their subsequent impact, this study provides a rational basis for coordinating multiple resources for desired outcomes. As such, this study is also aligned with the theoretic lens of resource orchestration and presents a promising methodological basis for reinforcing RBV and expanding its boundaries (Hughes et al., 2018).

5.3 Practical implications

In addition to the contingent aspect of capabilities, one of this study’s noteworthy achievements lies in the exploration of the synergistic effect of the simultaneous deployment of resources and the quantification of the effect into scalar measures beyond the conventional categorization of complementarity and substitution. In fact, the notable findings on the interplay of joint factors and their synergistic effect, alongside their individual influences, also contribute to the
literature by highlighting substantial pragmatic implications. Indeed, the effective utilization of multiple resources has long been a challenge for industry managers, in addition to being an arduous task for academicians. Specifically, a search for the optimal mix of resources is a core challenge due to the dilemma of balancing multiple resources, conflicting or cooperating, under the imposed contingency (Hughes et al., 2018; Martin et al., 2017). However, as highlighted in Figure 5, the proposed analytic process can predict the joint impact of combined resources and suggest to industry managers what might be an optimal mix of committed resources. For example, the optimal synergy of advertising and exports predicted at the 4% level of joint increases for high-capability firms shows the potential benefit of the proposed approach as a meaningful decision-support tool for industry managers.

In addition, the analytic process provides scientific control mechanisms to managers, particularly with respect to harmonizing multiple resources and setting achievable goals, thereby enhancing managerial proficiency and benchmarking capabilities. In general, benchmarking, as a systematic learning process, encompasses three core steps, such as selecting the target, determining the performance gap and pursuing improvements to fill the gap (Ayabakan et al., 2017; Dodd et al., 2023; Sangwan and Choudhary, 2018; Yang et al., 2015). In this sense, the segmentation of firms into relative capabilities and predicting the potential impact on shareholder value gives managers flexibility in identifying a target group, harmonizing resources and pruning the process to achieve actionable goals (Kwon et al., 2016; Lee et al., 2019). Moreover, the two-group segmentation categorized by a MLP decision surface adds new insight into the initial framing of a process for identifying a benchmark (e.g. high-capability firms) and determining the desired level of achievement. Along with the pragmatic benefit of the proposed approach, the empirical design of this study shows the prospective application of the MLP as a nonparametric machine learning technique and alternative to optimization tools such as DEA (Ayabakan et al., 2017; Yang et al., 2015) for assessing the relative efficiency of firms and predicting capability indices (Agarwal, 2016; Kwon et al., 2018; Molinos-Senante and Maziotis, 2022; Santin et al., 2004).

5.4 Concluding remarks
Like other studies, this research has several limitations but also suggests numerous opportunities for future research. The empirical setting was limited to large USA manufacturing industries, thereby raising questions about generalization. Hence, future research could diversify the empirical settings and experiments to different industry and country settings. In this study, we used general capabilities as a relative productivity measure for primary resources and performance. With the notion of rich definitions and conceptualizations of capabilities, it would be worth exploring alternative measures of specific capabilities (e.g. networking, operations and innovation) and subsequent moderation with selected factors (Gupta and Chauhan, 2021; Kouropalatis et al., 2019; Yang et al., 2015). Moreover, with a central focus on capabilities, the two-stage process of assessing the relative impact of strategic resources on capabilities will result in meaningful findings from both theoretical and managerial perspectives. This study used intensity measures for key factors; however, another meaningful advancement would include the expansion of R&D into technological capabilities and advertising into marketing capabilities as a comprehensive representation of input-output productivity measures (Ayabakan et al., 2017; Jacobs et al., 2016; Yang et al., 2015; Yu et al., 2018). Although the application of ANN to explore capabilities is still emerging, it would be worth comparing ANN to other machine learning techniques such as support vector machines (Moragues et al., 2023; Valero-Carreras et al., 2021). In this effort, empirical analysis using larger sample sizes and a comparative analysis of different industry sectors (e.g. manufacturing and services) and firm sizes (e.g. both large and small and medium enterprises) would result in interesting outcomes.
References


Interplay of R&D, advertising and exports


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