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**Previsão de Demanda de Produtos Novos: Uma Abordagem Híbrida Baseada
em Inteligência Artificial Explicável**

Florianópolis/SC

2025

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PREVISÃO DE DEMANDA DE PRODUTOS NOVOS: UMA ABORDAGEM HÍBRIDA
BASEADA EM INTELIGÊNCIA ARTIFICIAL EXPLICÁVEL

Dissertação submetida ao Programa de Pós-Graduação em Engenharia de Produção da Universidade Federal de Santa Catarina como requisito para a obtenção do título de Mestre em Engenharia de Produção.

Orientador: Prof. Enzo Morosini Frazzon, Dr.-Ing.

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O presente trabalho em nível de mestrado foi avaliado e aprovado por banca examinadora composta pelos seguintes membros:

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“O saber não está na ciência alheia, que se absorve, mas, principalmente, nas ideias próprias, que se geram dos conhecimentos absorvidos, mediante a transmutação por eles operada no espírito que os assimila.”

— Rui Barbosa

Resumo

Previsões de demanda são essenciais para o planejamento eficaz da cadeia de suprimentos, sobretudo no contexto de novos produtos, marcado por elevada incerteza devido à ausência de histórico de vendas. Este trabalho introduz um modelo híbrido de previsão de demanda combinando dois modelos preditivos e técnicas de Inteligência Artificial Explicável (XAI), com o objetivo de aumentar a clareza, a confiabilidade e a interpretabilidade das estimativas, de modo a subsidiar decisões gerenciais mais seguras.. Inicialmente, na primeira etapa do trabalho foi conduzida uma revisão sistemática da literatura para examinar a aplicabilidade dos métodos quantitativos, especialmente com o surgimento da Inteligência Artificial nas previsões de demanda de novos produtos. Em seguida, desenvolveu-se uma abordagem de IA que suprisse lacunas de informação nas previsões observadas na literatura, sendo avaliado em um cenário real de demanda de veículos elétricos no Brasil. O modelo sugerido empregou recursos XAI para tornar os resultados auditáveis, detectar vieses e orientar melhorias iterativas do processo preditivo. Os resultados empíricos indicam que o modelo híbrido superou consistentemente os modelos base isolados em métricas usuais de acurácia, confirmando sua capacidade preditiva. As explicações geradas mostraram-se coerentes e informativas, permitindo identificar os preditores mais influentes e apoiar decisões sobre lançamento e posicionamento de novos produtos. Em conjunto, os achados comprovaram a eficácia da abordagem proposta e avançaram o estado da arte em previsão de demanda para produtos recém-lançados, além de oferecerem evidências práticas para sua adoção em contextos organizacionais.

Palavras-chave: Inteligência Artificial Explicável. Previsão de Demanda. Produtos Novos.

Abstract

Demand forecasting is crucial for efficient supply chain planning, especially for new items, which demonstrate significant uncertainty due to the lack of sales history. The present study developed a hybrid demand-forecasting model that integrates two predictive models with procedures from Explainable Artificial Intelligence (XAI), aiming to improve the transparency, reliability, and interpretability of estimates to facilitate safer managerial decision-making. A thorough literature analysis was undertaken to assess the relevance of quantitative methodologies, particularly considering advancements in Artificial Intelligence, for demand forecasting of new items. An AI-driven methodology was devised to rectify information deficiencies identified in the literature and was assessed in a practical context concerning the demand for electric vehicles in Brazil. The suggested model utilised XAI approaches to ensure results are auditable, identify biases, and provide iterative enhancements to the forecasting process. The empirical findings demonstrated that the hybrid model frequently surpassed standalone baseline models on conventional accuracy metrics, validating its predictive efficacy. The generated explanations were coherent and instructive, facilitating the identification of the most significant predictors and aiding decisions concerning the introduction and positioning of new items. The findings collectively illustrated the efficacy of the suggested method and enhanced the existing standards in demand forecasting for newly introduced items, while also offering empirical support for its use in organisational settings.

Keywords: New Product Demand Forecasting, Explainable Artificial Intelligence

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1 INTRODUÇÃO

1.1 Contextualização

Previsões de demanda consistem na base de qualquer planejamento da cadeia de suprimentos. Em um processo de produção empurrada, a antecipação à demanda do cliente possibilita que o gestor planeje o nível das atividades como transporte, produção, estoque ou qualquer outra que necessite de controle e preparação (CHOPRA; MEINDL, 2007). Previsões precisas, resultam em economias financeiras significativas, maior competitividade, melhores relacionamentos na cadeia de suprimentos e maior satisfação do cliente (MOON; MENTZER; SMITH, 2003). Em contrapartida, erros na previsão são frequentemente amplificados para toda cadeia de suprimentos devido ao efeito chicote causado por demandas que não condizem com a realidade (ARVAN, 2019). Em vista disso, métodos baseados em Inteligência Artificial têm apresentado uma excelente alternativa frente aos métodos tradicionais de previsão.

Ingle (2021) classificou as diferentes abordagens de previsão de demanda em 4 categorias: Modelos Estatísticos Tradicionais, Modelos de Aprendizagem de Máquina, Modelos de Aprendizagem Profunda e Modelos Híbridos. A primeira categoria aborda os modelos tradicionais que fundamentam suas previsões primordialmente em dados históricos de vendas e empregam métodos de previsão de séries temporais, tais como ARMA (Auto Regressive Moving Average), ARIMA (Auto Regressive Integrated Moving Average) e Holt-Winters. Os modelos de aprendizado de máquina, por sua vez, são fundamentados em algoritmos capazes de aprender e aprimorar-se mediante a incorporação de dados. No contexto da previsão de demanda, esta técnica é amplamente utilizada para antecipar a quantidade de um produto a ser adquirido, proporcionando previsões mais precisas em comparação aos modelos tradicionais. Exemplificando algoritmos dessa categoria, destacam-se a Regressão Linear, Regressão Logística, K-vizinhos mais próximos (KNN), entre outros. Abordagens baseadas em aprendizado profundo demonstram eficácia em lidar com grandes volumes de dados, inclusive aqueles de natureza não linear e de diferentes formatos. Modelos como LSTM (Long Short-Term Memory), MLFANN (Multilayer Feedforward Artificial Neural Network) e GAN (Generative Adversarial Network) ilustram alguns exemplos dentro desta classe de aprendizado profundo. Por fim, os modelos híbridos incorporam a combinação de diferentes abordagens, utilizando os pontos fortes de cada modelo visando uma estrutura mais robusta e capaz de capturar informações em cenários diferentes.

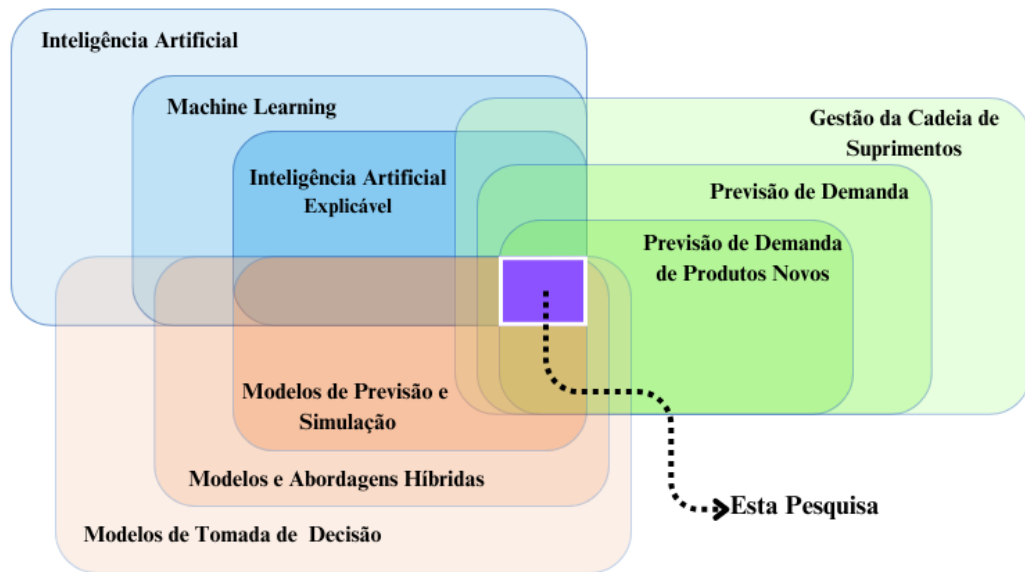
Importante salientar sobre estes recursos, que apesar de utilizar dados históricos

de vendas, as demandas dos clientes não são exatamente traduzidas como as vendas. Consequentemente, a inserção de informações de um analista nas ferramentas de previsão de demanda se torna importante para que realizem os ajustes adequados nos modelos, através de conhecimento prévio que dispõem (FILDES; GOODWIN, 2021; TONG; FEILER, 2017). Por outro lado, ao prever a demanda de um produto novo no mercado, onde não há dados históricos suficientes, o papel do gestor se torna ainda mais relevante (GOODWIN; MORITZ; SIEMSEN, 2019). Outrossim, um modelo estatístico com resultados interpretáveis no domínio da previsão de demanda também ajudam gestores a compreender quais dos atributos do modelo são maiores impulsionadores na determinação da demanda esperada, identificação de vieses no modelo e, também, na transparência das informações entre os elos da cadeia de suprimento (ROŽANEC; FORTUNA; MLADENIĆ, 2022; SANDERS; GRAMAN, 2016).

A participação ativa dos gestores nos modelos de previsão de demanda representa um recurso de grande importância para suplantando as lacunas de incerteza que os modelos matemáticos não conseguem abordar, sobretudo no contexto de produtos com pouco ou inexistente histórico de vendas. Nesse cenário, a literatura acadêmica disponibiliza uma extensa quantidade de estudos sobre o julgamento humano nas previsões, com o objetivo de fornecer uma base sólida para a minimização de equívocos. Entretanto, Van Den Broeke (2019) analisaram os ajustes de especialistas em quatro empresas, onde foi possível concluir que mesmo com um número elevado de ajustes por julgamento e correções mais positivas, de fato essas correções não eram tão precisas a ponto de melhorar a previsibilidade do modelo, podendo inclusive prejudicar as previsões. Nesse contexto, outras pesquisas indicam que, embora a previsão estatística seja apropriada para determinadas situações, os gestores frequentemente manifestam uma preferência por métodos baseados no julgamento humano. Tal preferência visa assegurar a possibilidade de intervenção, ocorrendo em até 90% dos casos (FILDES et al., 2009; SROGINIS; FILDES; KOURENTZES, 2023; TRAPERO, 2013). Portanto, é evidente que a simples interferência humana com informações, não garante que o modelo terá correções úteis que acabarão por melhorar o poder preditivo.

Diante do exposto, a Figura 1 localiza conceitualmente a pesquisa nas temáticas abordadas neste projeto, identificando a relação entre áreas de previsão de demanda de produtos novos em cadeias de suprimento, técnicas de inteligência artificial explicável e modelos de previsão baseado em simulação. Através da interligação estruturada destes temas, o presente estudo aborda o desenvolvimento de uma nova abordagem de previsão de demanda que transmita melhor clareza aos gestores nos momentos de decidir sobre a comercialização de novos produtos, mesmo em situações em que não estão dispostos dados suficientes de vendas para introduzir nos modelos tradicionais de previsão.

Figura 1 – Contextualização da pesquisa por área temática



1.2 Delimitação do problema de pesquisa

A presente pesquisa delimita-se ao problema de prever a demanda de produtos novos sem histórico de vendas, em contextos de alta incerteza, conciliando *precisão* e *interpretabilidade* do modelo. Parte-se do entendimento de que, para aprimorar previsões estatísticas, é necessário (i) avaliar se os resultados requerem ajustes e (ii) definir a direção e a magnitude desses ajustes (LAWRENCE, 2006). Em modelos de aprendizagem de máquina, essa tarefa é dificultada pela natureza de “*caixa-preta*”, que restringe a compreensão do porquê das estimativas (SHAMS AMIRI, 2021). Nesse cenário, métodos de explicabilidade, como o LIME Ribeiro, Singh e Guestrin (2016), tornam-se relevantes por fornecerem evidências sobre a contribuição de variáveis e, portanto, subsídios para o primeiro passo (diagnosticar quando e por que ajustar).

Ao mesmo tempo, a etapa de ajuste envolve informações contextuais que extrapolam o escopo dos modelos estatísticos, pois decorrem do conhecimento humano — intuição, experiência e dados adicionais (NILES PERERA, 2019). Tais intervenções, contudo, podem introduzir vieses e degradar a qualidade das previsões quando aplicadas sem critério: Fildes et al. (2009) mostram que muitos ajustes empresariais são triviais, por vezes na direção errada e acima da demanda real. Assim, o problema mais evidente que este estudo enfrenta é: como aprimorar a participação ativa de tomadores de decisão em modelos complexos de previsão de demanda de produtos novos.

Diante disso, a pesquisa limita-se a propor e avaliar um modelo híbrido explicável que combine componentes preditivos e técnicas de Inteligência Artificial Explicável para apoiar o diagnóstico e a justificativa de ajustes, mantendo transparência do processo. A

validação empírica concentra-se no mercado de veículos elétricos no Brasil, escolhido por sua dinâmica e variabilidade de adoção. Não se abordam, neste escopo, problemas de otimização subsequentes (estoques, preços ou logística); o foco permanece na previsão explicável da demanda e no apoio ao julgamento gerencial, de modo a reduzir a incerteza em lançamentos e a qualificar intervenções humanas sobre os resultados do modelo.

1.3 Objetivos

1.3.1 Objetivo Geral

Desenvolver um modelo híbrido, baseado em inteligência artificial explicável, para previsão de demanda para produtos novos.

1.3.2 Objetivos Específicos

Considerando o desenvolvimento do trabalho e o objetivo geral apresentado, desdobram-se os seguintes objetivos específicos:

- Identificar as principais técnicas e algoritmos de Inteligência Artificial utilizados na previsão de demanda de produtos novos e examinar sua aplicabilidade e eficácia. Ademais, apresentar direções futuras de estudos nessa área;
- Propor um modelo de previsão de demanda explicável para tomada de decisão sobre produtos novos;
- Avaliar o desempenho do modelo de previsão de demanda proposto, em função da explicabilidade e precisão dos resultados;

1.4 Estrutura do trabalho

Este trabalho de Dissertação de mestrado está estruturado da seguinte maneira: A próxima seção apresenta o referencial teórico, estabelecendo os conceitos e teorias fundamentais dos temas abordados no estudo, como previsão de demanda de produtos novos, julgamento humano em previsões de demanda e Inteligência Artificial Explicável. A Seção 3 aborda os métodos, técnicas e detalhamento dos procedimentos utilizados na condução da pesquisa. A Seção 4 trata-se do primeiro artigo que compõem a dissertação, intitulado: Exploring the Impact of Artificial Intelligence on New Product Demand Forecasting. Na Seção 5, o modelo conceitual utilizado nas próximas fases do estudo é apresentado. A Seção 6 descreve as macro atividades e o cronograma de desenvolvimento, delineando o planejamento do projeto. Por fim, a Seção 7 discute os resultados esperados, destacando as contribuições e implicações desta pesquisa.

2 Referencial Teórico

2.1 Previsão de demanda de produtos novos

Diferentemente dos produtos já consolidados, a previsão da demanda para novos produtos enfrenta desafios consideráveis devido à falta de histórico de vendas e às incertezas associadas à sua adoção pelos consumidores (BAARDMAN et al., 2018; LEE et al., 2014). Dito isso, considera-se improvável prever quantitativamente a procura de novos produtos e os métodos qualitativos podem apresentar vantagens na prática (KLASSEN; FLORES, 2001). Diversas abordagens analíticas se fundamentam na teoria da difusão como alternativa, sendo que o modelo Bass, por exemplo, abarca as fases iniciais da adoção de um novo produto por uma população. Este modelo é amplamente utilizado para modelar e compreender o processo de difusão de inovações, fornecendo insights sobre a taxa de adoção inicial e o crescimento subsequente no mercado (LINTON, 2002; SULTAN; FARLEY; LEHMANN, 1990).

Algoritmos de aprendizado de máquina podem capturar padrões que são difíceis para os humanos delinearem mental ou heurísticamente. No entanto, esses algoritmos são orientados por dados e exigem quantidades significativamente grandes de dados de treinamento (YAMAMURA et al., 2022; YU; SIMOFF; JAN, 2011). Tratando da previsão de novos produtos, Kahn (2002) afirma que, normalmente, não buscam precisão numérica porque não é possível obtê-la devido à escassez de dados. Por outras palavras, os gestores sabem que as previsões estão numericamente “equivocadas”, mas podem ser suficientemente boas para apoiar a compreensão e a tomada de decisões, com uma aproximação razoável (YAMAMURA et al., 2022).

Yamamura et al. (2022) propõem um estudo que utiliza do conhecimento do gestor para mitigar parcialmente a falta de dados em simulações de aprendizado de máquina, focando em produtos com produção em massa, como carros, celulares e microcomputadores. O estudo utiliza de uma abordagem híbrida de conhecimento de domínio do gestor e machine learning. Enquanto isso, Yan e Hu (2023) consideraram solucionar a falta de dados através da utilização do recurso da comunicação entre clientes, boca-a-boca (WOM), tanto em produtos do mesmo fabricante, quanto para produtos de fabricantes diferentes. Gestores valorizam cada vez mais o boca-a-boca do consumidor para aprimorar a previsão de demanda e ajustar estratégias de produção. Para tanto, utilizaram Modelagem e Simulação Baseada em Agentes (ABMS) e o modelo Bass para ajustar métodos de previsão de demanda, através do WOM entre produtos, e propor estratégias de ajuste da capacidade de produção.

Van Steenbergen e Mes (2020) apresenta o método denominado DemandForest, que recorre a algoritmos como K-means, Random Forest e Quantile Regression Forest para realizar previsões de demanda de produtos novos. Essa abordagem, fundamentada em técnicas de aprendizado de máquina, integra dados históricos de vendas de produtos anteriormente lançados, bem como características de produtos existentes e novos, a fim de efetuar previsões prévias ao lançamento e oferecer suporte às decisões de gerenciamento de estoque para produtos recém-introduzidos no mercado.

2.2 Julgamento humano em previsões de demanda

Alguns estudos têm buscado oferecer auxílio para que analistas tomem melhores decisões nos ajustes dos modelos estatísticos de previsão. O conceito de "previsão por julgamento" tem sido empregado na literatura para englobar diversos significados e procedimentos distintos, abrangendo desde previsões puramente baseadas em julgamento, ajustes estatísticos de previsões derivadas de julgamento, até a combinação de previsões que envolvem tanto aspectos estatísticos quanto de julgamento humano (NILES PERERA, 2019). A adaptação das previsões estatísticas por meio de julgamento representa uma alternativa significativa à combinação de abordagens de previsões estatísticas e julgamento humano, abrangendo métodos que variam desde simples médias de previsões componentes até abordagens bayesianas. Várias pesquisas na indústria têm evidenciado que a prática de ajuste de previsões estatísticas por julgamento é comum e amplamente adotada (LIN; GOODWIN, 2014).

A recomendação feita por Wibowo (2023) é que os ajustes por julgamento só devem ser feitos quando tiver disponível informações contextuais específicas ou quando o uso de modelos estatísticos se tornar menos razoável, como em situações com alto grau de incerteza. Com esse propósito, buscou desenvolver um método para determinar a melhor política de revisão das previsões estatísticas. O estudo demonstra que a metodologia de aprendizagem de políticas pode oferecer recomendações valiosas aos analistas para melhorar o processo de revisão, com menos interferência inadequada ou por vezes indiferentes. Para tal, utilizaram um modelo de árvore de decisão com três ações alternativas, “não fazer nada”, “seguir o julgamento” ou “média simples”.

No estudo conduzido por Alvarado-Valencia et al. (2017) foi recomendado que ajustes nas previsões sejam efetuados exclusivamente em situações em que os analistas possuam uma expertise significativa, ao passo que a confiança nos modelos estatísticos se encontre em um patamar inferior. Esse direcionamento sugere uma abordagem seletiva, priorizando a intervenção humana quando a experiência se revela mais crítica que a confiança nos modelos. Adicionalmente, no estudo de Goodwin (2000), destaca-se a aceitação de métodos mais intuitivos para aprimorar as previsões, exemplificando a prática de registrar

as razões subjacentes às modificações no modelo em um documento. Essa abordagem não apenas oferece transparência no processo de ajuste, mas também proporciona um registro documentado das decisões tomadas, facilitando a análise retrospectiva e aprimoramento contínuo do modelo. A combinação de julgamento humano, fundamentado na experiência, e métodos intuitivos fornece uma abordagem mais holística para otimizar as previsões em cenários nos quais a confiabilidade nos modelos estatísticos é percebida como limitada.

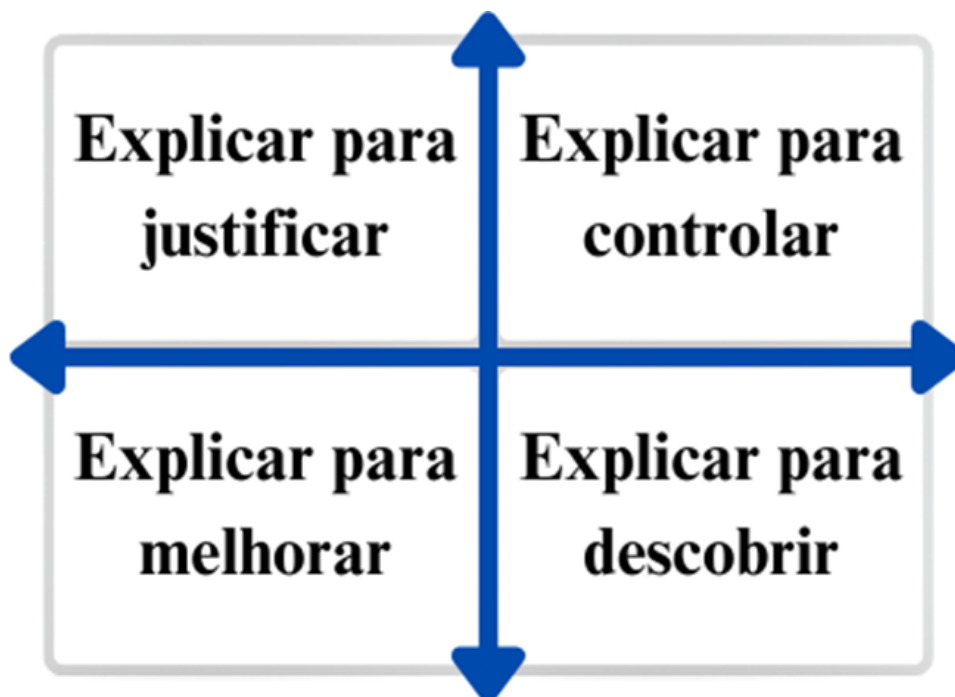
2.3 Inteligência Artificial Explicável (XAI)

A problemática da "caixa preta" em Inteligência Artificial refere-se à complexidade que um sistema apresenta ao fornecer uma explicação compreensível sobre o processo decisório que levou a uma determinada conclusão (ALI et al., 2023). A partir disso, o propósito da pesquisa em XAI, neste cenário, consiste em aprimorar a compreensibilidade e transparência dos sistemas sem comprometer seu desempenho, fornecendo explicações sobre as decisões do modelo, identificando possíveis distorções ou problemas nos dados de treinamento e garantindo que os algoritmos funcionem conforme o esperado (ADADI; BERRADA, 2018; SHAMS AMIRI, 2021).

A Agência de Projetos de Pesquisa Avançada de Defesa (DARPA) introduziu o termo "Explainable AI" (XAI), frequentemente denominado como "Caixa Branca". Essa nomenclatura reflete a capacidade do XAI em elucidar o processo interno do modelo, proporcionando uma compreensão mais aprofundada sobre como as decisões são alcançadas (SARANYA; SUBHASHINI, 2023). Um modelo interpretável é um modelo onde um usuário pode não apenas observar, mas também determinar e compreender matematicamente a relação entre entradas e saídas (DORAN; SCHULZ; BESOLD, 2017). O princípio da explicabilidade está intrinsecamente vinculado ao da interpretabilidade. Métodos interpretáveis são considerados explicáveis quando suas operações podem ser compreendidas por seres humanos. Embora o termo "explicável" seja proeminente na terminologia da Inteligência Artificial Explicável (XAI), o termo "interpretável" é adequado nessa questão (ALI et al., 2023).

A adoção da tecnologia de Inteligência Artificial Explicável (XAI) emergiu como um recurso crucial em diversas áreas do conhecimento, especialmente em contextos nos quais a confiança plena nos resultados de modelos tradicionais não é viável. A Figura 2 apresenta quatro razões principais pelas quais a implementação de um modelo XAI se revela útil. No contexto de "explicar para justificar", os modelos são empregados para fornecer informações relevantes em situações críticas do mundo real. A abordagem de "explicar para controlar" transcende as justificativas, focalizando na prevenção de vieses e falhas no modelo. Além disso, um modelo explicável desempenha um papel crucial no processo de aprimoramento contínuo e pode contribuir para a descoberta de novos

Figura 2 – Necessidade de um modelo XAI



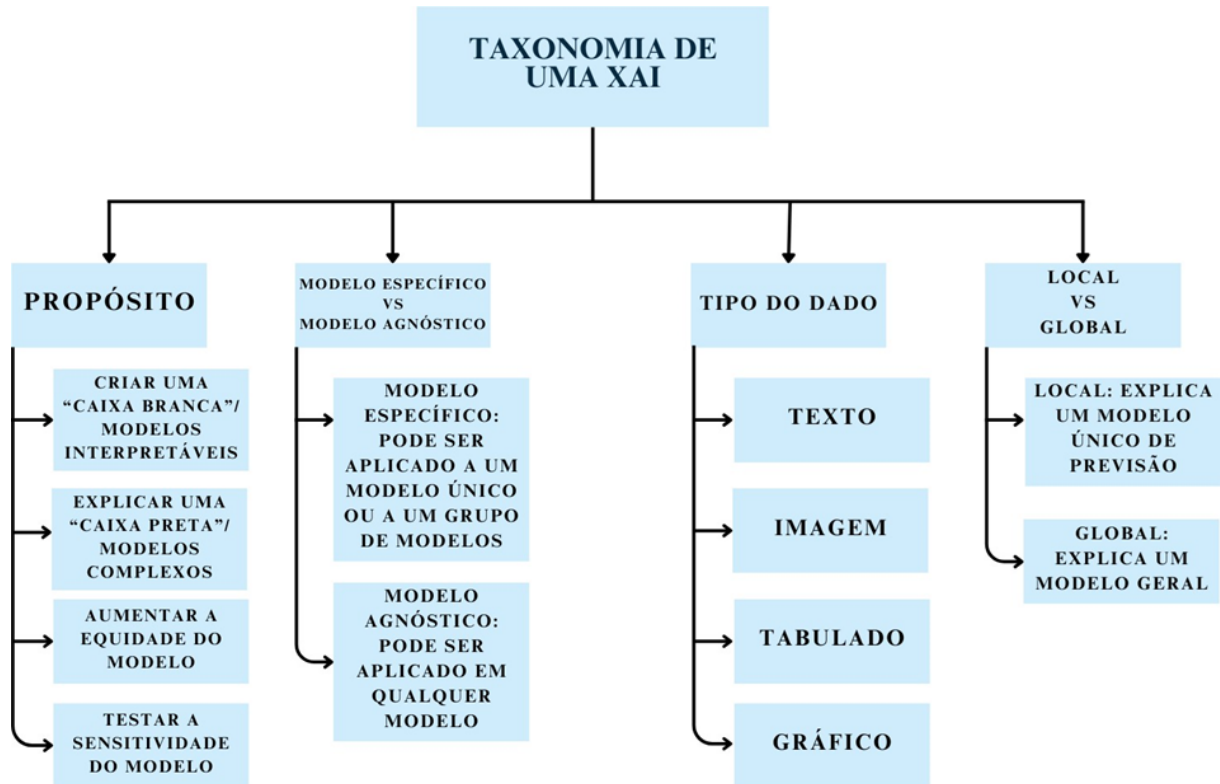
Fonte: Adaptado de Saranya e Subhashini (2023)

insights sobre o problema, adquirindo conhecimento por meio da coleta e interpretação de informações.

A Figura 3 apresenta a Taxonomia de uma Inteligência Artificial Explicável (XAI), adaptada de Linardatos, Papastefanopoulos e Kotsiantis (2021), delineando os diversos aspectos pelos quais um método interpretável pode ser categorizado. Essas propriedades assumem relevância significativa durante o processo de seleção do modelo mais apropriado para abordar a problemática em questão. É imperativo considerar essas nuances taxonômicas para assegurar a escolha do modelo mais adequado às exigências e objetivos do cenário em análise.

Ao tratar do tipo de algoritmo utilizado para interpretabilidade do modelo, classifica-se a partir do funcionamento de cada abordagem. Quando o modelo XAI vem acompanhado da explicação, e não requer nenhuma ferramenta específica para isso, é chamado de modelo “Ante- hoc”. Em contrapartida, modelos “Post-hoc”, requerem uma abordagem adicional para extrair explicações (SARANYA; SUBHASHINI, 2023). Essa categoria de modelos é separada em Específicos ou Agnósticos, conforme ilustrado na Figura 3, e refere-se à distinção entre sua aplicação específica para um algoritmo particular ou sua aplicabilidade a qualquer algoritmo possível. Complementarmente, a classificação do método utilizado pode ser distinguida com base em sua capacidade de fornecer explicações. Se o método fornece explicações apenas para uma instância específica do modelo, é categorizado como “Local”. Por outro lado, se o método é capaz de explicar o modelo como um todo,

Figura 3 – Taxonomia da abordagem conceitual da XAI



Fonte: Adaptado de Linardatos, Papastefanopoulos e Kotsiantis (2021)

independentemente de instâncias individuais, é classificado como “Global”.

O propósito subjacente à concepção e aplicação de métodos XAI, constitui uma característica essencial a ser minuciosamente avaliada. Dentro da subcategoria que se dedica à explicação de modelos de aprendizagem de máquina identificados como "caixa preta", o enfoque não reside na formulação de abordagens interpretáveis, mas sim na interpretação de modelos já existentes e previamente treinados. Nessa subcategoria específica, os modelos são classificados como "Post-hoc". A criação de algoritmos "caixa branca" refere-se ao desenvolvimento de modelos interpretáveis, exemplificados por algoritmos de Árvore de Decisão. A promoção da equidade no modelo representa um objetivo categorizado no âmbito do impacto social e ético dos algoritmos de aprendizagem de máquina. A garantia da transparência do modelo de IA, em particular, contribui de maneira significativa para a mitigação de vieses e para a aceitação social dessas tecnologias. Por fim, a avaliação da confiabilidade das previsões constitui a última subcategoria no contexto do propósito de uma XAI.

2.3.1 Requisitos para um modelo de Inteligência Artificial Explicável

Um modelo de Inteligência Artificial Explicável baseia-se na ideia de fornecer apoio para especialistas no sentido de compreensão, confiabilidade e eficiência nos resultados de uma IA. Entretanto, para garantir que esse sistema seja explicável deve-se cumprir alguns

requisitos. Nimmy (2022) definiram estes requisitos como:

- Deve ser confiável: Para assegurar a confiabilidade dos dados e métodos utilizados, um modelo XAI deve garantir que as interpretações dos resultados são oriundos de dados confiáveis e não da imaginação (KORSTJENS; MOSER, 2018). Ademais, deve apresentar evidências de que estes resultados podem ser aplicados em outros contextos, situações, momentos e populações (SLEVIN; SINES, 1999).
- Deve ser completo: O modelo deve garantir que escolherá a melhor solução quando existirem diversas soluções, assim como deve fornecer uma solução quando houver apenas uma possível, e em seguida, encerrar (MOON, 2016).
- Operação transparente: A transparência de uma abordagem envolve mostrar como os dados estão sendo utilizados para tomar decisões ou fazer previsões, através de uma explicação clara sobre como o modelo trabalhou para atingir o objetivo (SITEK, 2015).
- Resultados interpretáveis: Capacidade de expressar os resultados com prova matemática e lógica (LINDLOF; TAYLOR, 2017). Como extensão da ideia de interpretabilidade, uma abordagem XAI deve ter a possibilidade de projetar um mapa mental para que possa visualizar o resultado de acordo com as demandas do usuário (PHILLIPS, 2011).

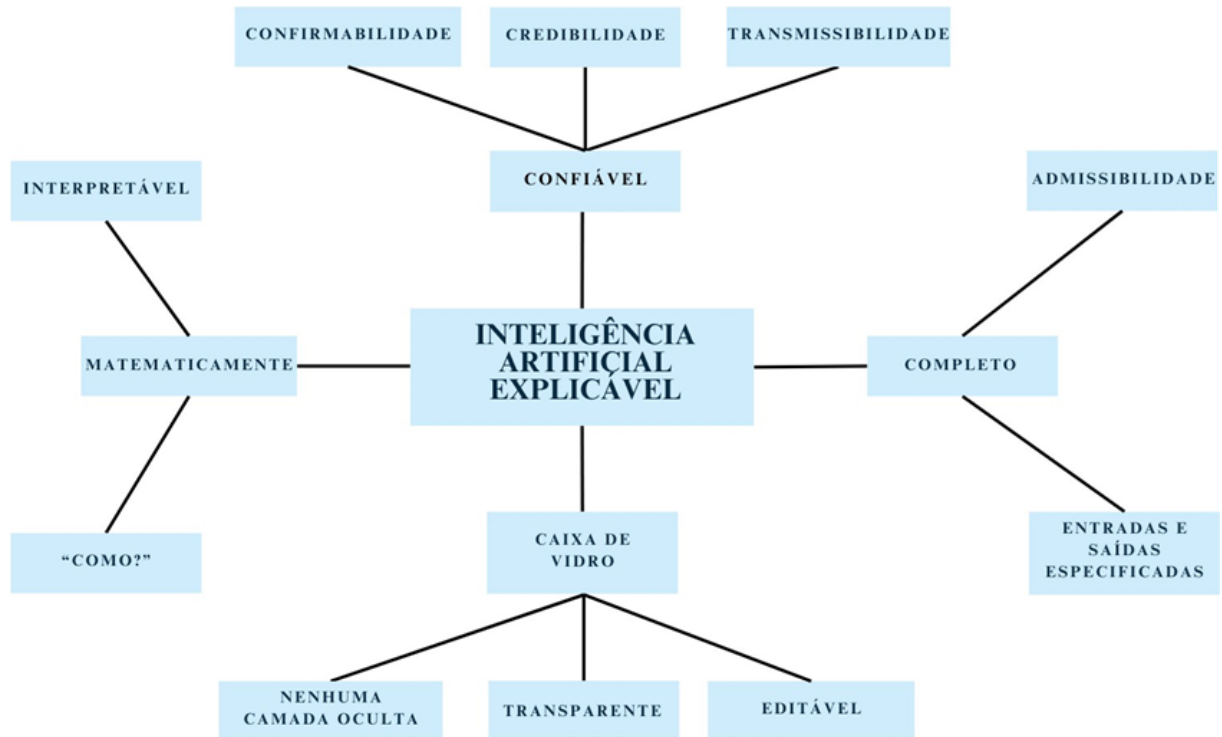
A Figura 4 oferece uma visão detalhada de características adicionais fundamentais para os requisitos de uma XAI, aprimorando a compreensão desses aspectos essenciais. A explicitação matemática da capacidade e eficiência do modelo é de suma importância para responder à indagação essencial de "Como?", facultando a interpretabilidade dos resultados. O conceito de um "Modelo Caixa de Vidro" se contrapõe ao de um "Modelo Caixa Preta", assegurando a ausência de camadas ocultas ao usuário, permitindo, assim, a manipulação e verificação transparente dos resultados e dos processos intermediários.

Essa abordagem não apenas destaca a importância da transparência, mas também realça a necessidade de edição e verificação do modelo, elementos cruciais para a confiabilidade e aceitabilidade de uma XAI.

2.3.2 Inteligência Artificial Explicável em previsão de demanda

É fundamental proporcionar explicações claras e compreensíveis nos modelos de previsão de demanda, pois tais esclarecimentos capacitam o planejador a alcançar três objetivos primordiais. Primeiramente, possibilitam a compreensão dos atributos do modelo que exercem influência significativa na determinação da demanda esperada. Além disso, auxiliam na identificação de eventuais vieses presentes no modelo. E, por fim, viabilizam a

Figura 4 – Recursos de uma metodologia de IA explicável



Fonte: Adaptado de Nimmy (2022)

compreensão do planejador sobre as possíveis melhorias a serem implementadas no modelo. Essa abordagem promove a transparência, interpretabilidade e aprimoramento contínuo dos modelos de previsão de demanda, contribuindo para decisões informadas e estratégias mais eficazes na gestão de cadeias de suprimentos (ROŽANEC; FORTUNA; MLADENIĆ, 2022).

Arboleda-Florez e Castro-Zuluaga (2023) utilizaram em sua pesquisa a metodologia SHAP como ferramenta explicativa para que gerentes e partes interessadas entendam as previsões e participem dos ajustes. O método SHAP, comparável a uma abordagem baseada em teoria dos jogos, visa aprimorar a interpretabilidade de previsões individuais por meio do cálculo de valores de significância para cada recurso. Esses valores SHAP, ao representarem um grau consolidado de importância do recurso, preservam três propriedades cruciais: precisão, consistência e ausência. Destaca-se que o SHAP é notável pela sua facilidade de cálculo e naturalidade interpretativa, proporcionando uma ferramenta eficaz para a compreensão aprofundada das previsões em contextos diversos (LINARDATOS; PAPASTEFANOPOULOS; KOTSIANTIS, 2021). Neste contexto, o método foi empregado para prever a demanda no setor de vendas diretas de produtos de vestuário. Os resultados da aplicação mostraram que a metodologia proposta melhorou a precisão das previsões e forneceu insights importantes sobre as interações multivariadas complexas que influenciam a demanda. Chen (2021) também utilizaram a metodologia SHAP para interpretar seu modelo de Rede Neural empregado na previsão de 28 dias de vendas da Walmart, o que

garantiu que os resultados apresentassem resultados superiores em comparação com outros modelos de aprendizagem de máquina.

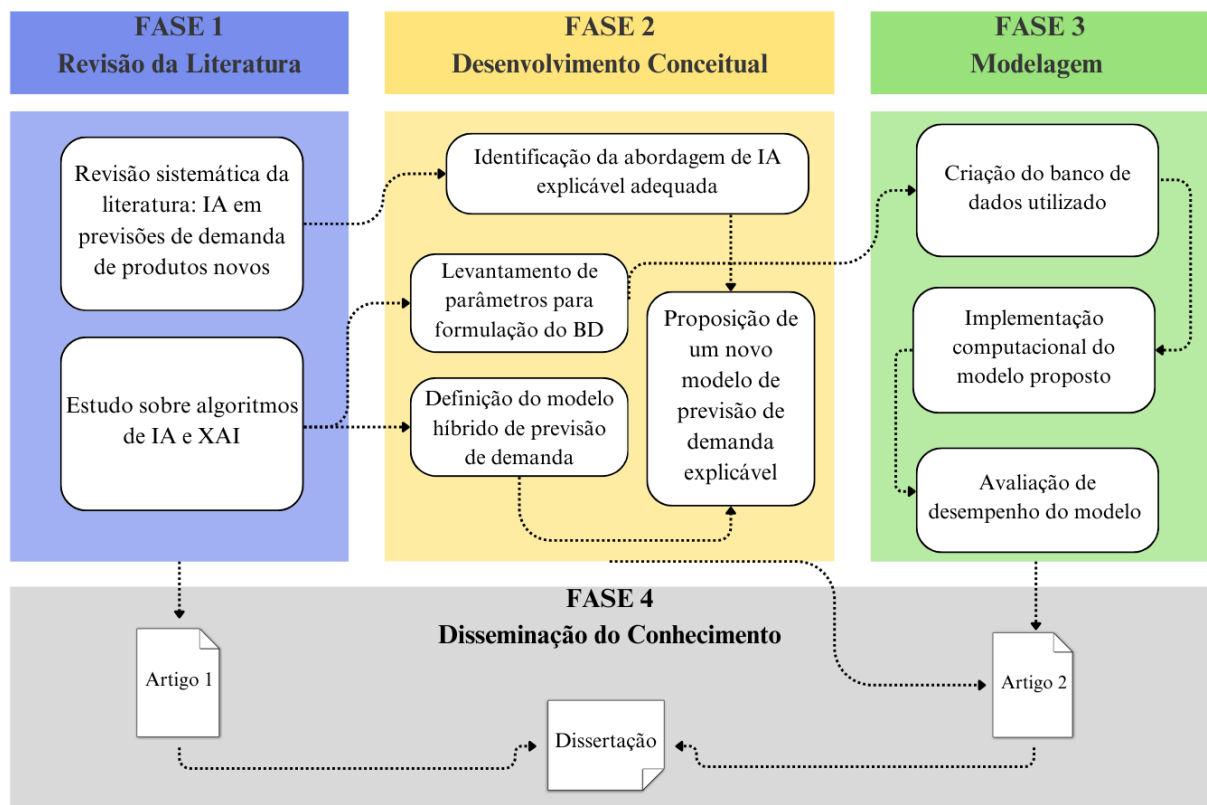
Uma abordagem interessante é a chamada “Knowledge Graph”, proposta por Rožanec, Fortuna e Mladeníć (2022). Essa arquitetura de inteligência artificial explicável difere das demais por utilizar tecnologias semânticas e eventos de mídia para construir contexto e fornecer explicações das previsões realizadas enquanto recomenda fontes de dados adicionais que poderiam ser utilizadas para enriquecer o conjunto de dados existente. O Knowledge Graph melhora a qualidade das explicações na previsão de demanda, ao permitir a identificação de quais pistas correspondem a conceitos semanticamente próximos e quais variáveis os gestores podem ajustar, respaldando informações do conjunto de dados e sistemas internos. Os resultados são apresentados por meio de uma interface gráfica de usuário que exibe uma explicação multi-parada, onde os componentes são exibidos ou ocultados com base nas informações relevantes para o usuário final ou políticas de confidencialidade. A interface permite também, que o usuário visualize as previsões de demanda, a incerteza associada a elas e as explicações correspondentes.

3 Procedimentos Metodológicos

O delineamento desta pesquisa é composto por quatro fases principais, cada uma subdividida em etapas complementares, conforme detalhado de maneira elucidativa na Figura 5. Esta abordagem foi meticulosamente concebida para atingir os objetivos previamente delineados na Seção 2 deste trabalho. A Tabela 3, por sua vez, estabelece uma conexão clara entre esses objetivos e as fases correspondentes do estudo, proporcionando uma visão abrangente e organizada do planejamento e execução desta pesquisa.

Cabe destacar que, ao examinar a relação de dependência entre as tarefas apresentadas na Figura 5, alguns pontos merecem destaque. Algumas destas atividades, de acordo com a natureza do estudo, podem transcorrer de maneira simultânea, não requerendo a conclusão de certa atividade para início da próxima. Essa consideração proporciona uma flexibilidade maior na execução das atividades, otimizando o fluxo de trabalho e garantindo eficiência na consecução dos objetivos propostos. Assim, a estruturação cuidadosa dessas fases e etapas reflete a abordagem sistemática e rigorosa adotada neste estudo para assegurar a coerência e a eficácia na condução da pesquisa.

Figura 5 – Procedimentos metodológicos



Um detalhamento das fases da pesquisa é apresentado a seguir, com o intuito de esclarecer cada tarefa realizada e garantir a reprodutibilidade metodológica do estudo:

I. Revisão da Literatura: Ao tratar da previsão de demanda para produtos novos, gestores buscam confiar em pesquisas, intuição e heurísticas para solucionar o problema da falta de dados suficientes para os modelos tradicionais (YAMAMURA et al., 2022). Nesse contexto, a presente fase do estudo tem por objetivo analisar a aplicabilidade de métodos quantitativos utilizados na previsão de demanda de produtos novos, com foco nos avanços da Inteligência Artificial, por meio de uma Revisão Sistemática da Literatura. Paralelamente, será conduzida uma investigação sobre direções futuras nessa área, apresentando alguns dos principais pontos a ser explorado em pesquisas futuras. Com o atingimento desse objetivo, haverá uma base robusta para a formulação do método que será desenvolvido nas etapas subsequentes.

II. Desenvolvimento Conceitual: Nesta fase do estudo, alicerçada nas percepções e descobertas obtidas na etapa anterior, será definido o modelo de IA explicável a ser aplicado para abordar a problemática em questão. A escolha do modelo será fundamentada na eficácia comprovada em lidar com a interferência humana de maneira precisa e interpretável. Ao final desta etapa, será consolidado o modelo conceitual de previsão de demanda explicável, incorporando a abordagem XAI para reduzir incertezas neste cenário. Além disso, serão definidos os requisitos para formulação do Banco de Dados que utilizado na aplicação prática do método.

III. Modelagem: Na Fase 3, as diretrizes estabelecidas nas Fases 1 e 2 foram implementadas em um fluxo de trabalho computacional. A base de dados foi estruturada com base em atributos técnicos dos automóveis, critérios de segmentação de mercado e métricas regionais, contando com procedimentos de pré-processamento, como limpeza, tratamento de lacunas e padronização quando pertinente. A execução foi efetuada na linguagem Python, valendo-se de bibliotecas estabelecidas para a manipulação de dados e o aprendizado de máquina, como pandas e scikit-learn, além do pacote SHAP para a explicabilidade. A distinção entre o conjunto de treino e o de teste considerou a natureza temporal da questão, de forma a representar o contexto de previsão de demanda para automóveis elétricos no Brasil.

A proposta foi implementada como uma arquitetura híbrida: um classificador avalia a propensão ou adoção inicial, enquanto um regressor estima o volume condicional; as saídas são integradas por meio de empilhamento com um meta-modelo de Gradient Boosting. As explicações foram geradas por meio de valores SHAP, possibilitando a identificação dos preditores mais impactantes e a análise da consistência das relações estabelecidas. A avaliação levou em conta as linhas de base (modelos base isolados) e métricas convencionais de acurácia; os resultados indicaram ganhos consistentes do modelo híbrido, além de fornecer explicações úteis para apoiar decisões relacionadas a lançamento, precificação e posicionamento.

IV. Disseminação do conhecimento: Ao término da Fase 1 e da Fase 3, serão

desenvolvidos dois artigos com o propósito de disseminar e compartilhar o conhecimento adquirido ao longo desta pesquisa. Essas publicações visam não apenas documentar os achados significativos obtidos nas respectivas fases, mas também contribuir para o avanço do conhecimento na área abordada. O processo de elaboração desses artigos será pautado pela rigidez metodológica e pela exposição clara e concisa dos resultados, garantindo, assim, a qualidade e relevância científica das contribuições deste estudo.

Tabela 1 – Relação entre as fases da pesquisa e dos objetivos

Fase	Método	Objetivo Específico	Disseminação do conhecimento
1. Revisão da literatura	Revisão sistemática da literatura	I. Identificar as principais técnicas e algoritmos de Inteligência Artificial utilizados na previsão de demanda de produtos novos	Artigo 1
2. Desenvolvimento conceitual	Modelagem e Implementação computacional	II. Propor um modelo de previsão de demanda explicável para tomada de decisão sobre produtos novos	Artigo 2
3. Modelagem		III. Avaliar o desempenho do modelo de previsão proposto, em função da explicabilidade e precisão dos resultados	

A Tabela 3 estrutura, de maneira concreta, a coerência interna do estudo ao associar *Fase–Método–Objetivo–Disseminação do conhecimento*. Nota-se um encadeamento gradual, no qual cada fase atende a um objetivo particular e, simultaneamente, fornece recursos para a etapa subsequente, prevenindo a sobreposição de atividades e assegurando a rastreabilidade metodológica.

A Fase 1, fundamentada em uma revisão sistemática da literatura, atende ao primeiro objetivo específico da pesquisa e oferece a base conceitual que sustenta as decisões posteriores. Sua divulgação se concretiza no *Artigo 1*, destinado à síntese crítica da área de estudo. Com base nas observações obtidas na literatura, foi delineada a estrutura que será implementada na etapa seguinte. A Fase 2 atua como um vínculo de transição, fortalecendo a estrutura conceitual do modelo explicável (Objetivo II) e estabelecendo os requisitos do banco de dados, funcionando como uma conexão entre o diagnóstico inicial e a evidência empírica. Finalmente, a Fase 3 implementa a modelagem e realiza a avaliação (Objetivo III), produzindo os resultados aplicados que embasam o *Artigo 2*. Em conjunto, a tabela ressalta a lógica do percurso, desde a análise crítica até a implementação e validação, e detalha a forma como os resultados de disseminação estão interligados aos marcos do projeto.

4 Artigo 1: Exploring the impact of artificial intelligence on new product demand forecasting

Abstract:Forecasting demand for new products poses significant challenges for managers due to the scarcity of historical sales data, which limits the effectiveness of traditional forecasting methods. Historically, companies have relied on market research and judgment-based approaches to address this issue. Recently, however, there has been a shift towards exploring new quantitative techniques and alternative methods to enhance forecasting accuracy. The current study systematically analyses the applicability of quantitative methods employed in new product demand forecasting, focusing on the advancements offered by artificial intelligence (AI) techniques. We categorize the approaches into four distinct subgroups: diffusion and analogy models, statistical models, hybrid models, and AI-based models. This classification provides a structured perspective on the various methods and enables a comprehensive evaluation of each. Our research demonstrates how recent AI advancements contribute to robust demand forecasting under complex, data-limited conditions, presenting both innovative possibilities and certain limitations. This study underscores the transformative potential of AI in demand forecasting of new products, highlighting future directions focused on integrating big data, model explainability, and the development of hybrid approaches within forecasting practices.

Keywords:New Product, Forecast, Demand, Artificial Intelligence

4.1 Introduction

Introducing new products is vital for the success and survival of many companies. However, accurately forecasting demand for new products is extremely challenging for managers and decision-makers, with substantial costs associated with failures. Given its critical nature, numerous methods have been developed to aid in these forecasts. New product forecasting must address major issues such as data scarcity, non-linear relationships, and the uncertainty about consumer acceptance of breakthrough technologies. Consequently, it is regarded as one of the most difficult and crucial management tasks (GOODWIN; MEERAN; DYUSSEKENEVA, 2014; MAS-MACHUCA; SAINZ; MARTINEZ-COSTA, 2014).

There is a significant difference between forecasting demand for new products and forecasting demand for existing products. For established products, historical demand data can be accumulated over time, allowing for the creation of a detailed time series. In

contrast, new product forecasting lacks such historical data, making it difficult to rely on quantitative methods. Consequently, forecasting for new products often depends on qualitative methods and judgmental forecasting techniques, where experience, intuition, and expert opinions are used to generate forecasts in the absence of concrete data (KAHN, 2014).

Despite that, Goodwin, Dyussekenewa e Meeran (2013) assert that quantitative methods should be central to the forecasting process of new products. In this context, some quantitative methods for forecasting new products predominantly rely on forecasts by analogies to overcome the lack of historical demand data. These models use data from similar products to project forecasts for new ones. The underlying assumption of forecast by analogy is that similarities between products will result in comparable demand patterns. However, there is no assurance that the historical demand for analogous products will accurately reflect the future demand for new products (KAHN, 2014; STEENBERGEN; MES, 2020). Therefore many forecasting methods for new products continue to depend on expert opinions, surveys and the average sales of similar products (KAHN, 2002).

In light of these limitations, the rapid advancement of artificial intelligence in recent years has significantly contributed to addressing the challenges associated with forecasting demand for new products. Various forecasting models leveraging AI technologies have been developed to enhance accuracy beyond traditional models, even in the face of limited historical sales data. Consequently, this study aims to analyze the impact of artificial intelligence on new product demand forecasting through the exploration of the following research question:

Are artificial intelligence tools effective in forecasting demand for new products compared to traditional methods?

To examine this question comprehensively, this study has the following objectives: (1) Identify the main techniques and algorithms used in forecasting demand for new products, (2) Evaluate the performance of AI tools compared to traditional methods, and (3) Analyze the challenges and future opportunities for the development of forecasting demand for new products. The remainder of this paper is structured as follows: The subsequent section elaborates on the methodology employed in this study, detailing the procedures and techniques utilized. Section 4.3 presents a concise analysis of the study's data. Section 4.4 offers an in-depth discussion of the solutions proposed by the authors of the reviewed studies. In Section 4.5, we provide a comprehensive analysis of the results, emphasizing the key findings. Section 4.6 addresses future perspectives, and finally, Section 4.7 summarizes the conclusions drawn from our research.

4.2 Methodology

To analyze the application of Artificial Intelligence techniques in forecasting demand for new products across various scenarios and perspectives, this study employs a systematic review with a structured methodology. This approach ensures the inclusion of all relevant papers in our analysis and provides a robust framework for accurately screening, filtering, and evaluating the literature. (DRESCH; LACERDA; ANTUNES, 2015) outline a roadmap for conducting literature reviews, beginning with defining the research question and the conceptual framework guiding the study. This is followed by developing a search strategy, which includes specifying the search string, selecting relevant databases, and utilizing appropriate softwares. The next step involves defining the eligibility criteria for included papers. Once the dataset is established, the final stages involve assessing the quality of the studies and summarizing the results. This systematic method was adhered to in this study, ensuring the reproducibility and validity of the research.

4.2.1 Study Selection

The search string was developed based on the PICO strategy (ARAÚJO, 2020). This strategy involves constructing the search string using three key clusters: Population/Patient/Problem, the phenomenon of interest, and the context. Accordingly, the final Boolean search string was formulated as follows: (Cluster 1) AND (Cluster 2) AND (Cluster 3). The specific keywords for each cluster are defined in Table 2. These keywords were used to search through the databases Scopus, Web of Science, and the gray literature database Google Scholar.

Tabela 2 – Keyword search string

Cluster	Keyword
Cluster 1	"New product"OR "innovative product"
Cluster 2	"Artificial intelligence"OR "Machine learning"OR "neural network"OR "cnn"OR "deep learning"OR "hybrid"OR "fuzzy"OR "probabilistic"OR "time series"OR "Bayesian"
Cluster 3	(forecast* OR predict* OR estimation) AND (demand OR "New product forecasting"OR "Forecasting new product demand")

The database search was conducted in April 2024 and followed the PRISMA methodology (PAGE et al., 2021). This structured approach was employed to ensure a rigorous and transparent selection of studies for inclusion in this review, owing to its comprehensive and systematic framework. The initial search yielded 149 papers, with 108 from Scopus, 38 from Web of Science, and three from Google Scholar. Subsequent

screening removed 22 papers due to duplication and excluded ten additional documents for the following reasons: they were reviews, book chapters, or not written in English. Additionally, 11 papers that could not be accessed were also excluded.

In the final stage of the screening process, the abstracts and titles of the selected papers were reviewed to evaluate their relevance to our study. During this phase, eligibility criteria were applied to determine which studies should be included. These criteria are outlined in Table 3. Following the PRISMA methodology for study selection, 31 papers from the databases were included, along with three additional papers obtained from Google Scholar. The flowchart depicting this process is presented in Figure 6.

Tabela 3 – Eligibility Criteria

Inclusion Criteria	Exclusion Criteria
Empirical or case studies on new product demand forecasting	Product development or product design
Studies employing AI techniques	Not address demand forecasting
	Demand forecasting for non-new product

4.2.2 Quality Assessment

The assessment of the methodological quality of the papers aims to reduce the risk of biases, which could lead to errors in the conduct or analysis of the studies. To evaluate the quality of the papers, eight questions were defined based on the Joanna Briggs Institute framework (AROMATARIS et al., 2015). Each question was rated as "high quality, medium quality," or "low quality," with corresponding weights of 10, 7.0, and 4.9, respectively. Papers scoring below 50.0 were excluded from the review. The detailed questions used for this quality assessment are presented in Table 4.

4.3 Data Analysis

Following the analysis of the methodological quality of the selected studies in the previous stage, two papers were removed from the review for not meeting the predefined minimum score: "A Multi-Period Newsvendor Problem with Pre-Season Extension under Fuzzy Demand" (BEHRET; KAHRAMAN, 2010) and "Hybrid Model Building for Forecasting New Product Demand in Retail Chains" (BISWAL; DAS; MISHRA, 2019). These studies did not align with the quality standards required for this review. Consequently, the total sample was reduced to 32 reports.

Figura 6 – PRISMA

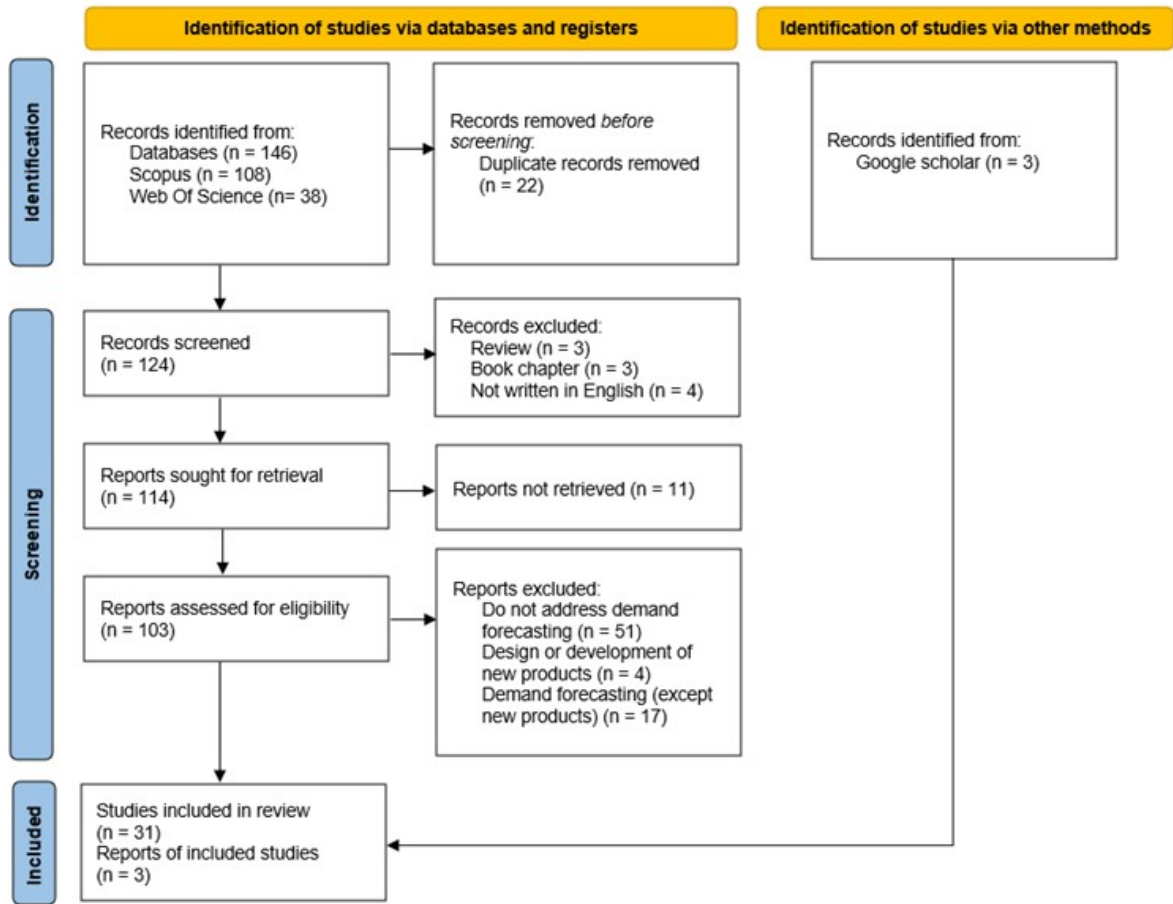


Figure 7 presents the performance of the papers across the eight evaluated questions. It is observed that, in Question 2 - "Are the techniques used explainable and easily interpretable?"— most of selected papers received lower-than-expected scores. This question pertains to the explainability of forecasting models, defined by Baur et al. (2024) as "the extent to which a human can reason about the factors influencing a model's prediction." This capability is crucial for enhancing model accuracy and precision, yet it remains insufficiently explored in new product demand forecasting. Similarly, as highlighted in Question 8, few papers address the practical applicability of the proposed solutions, an essential factor for ensuring their effectiveness.

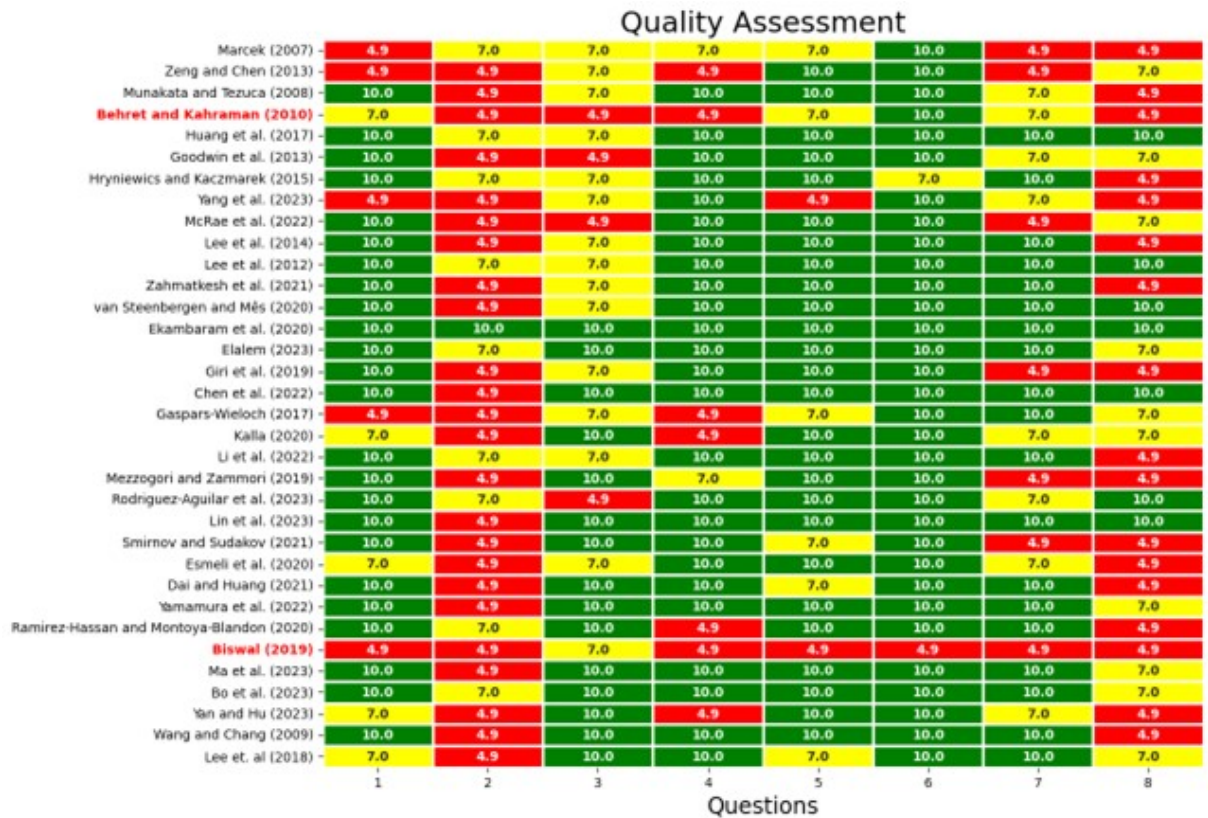
With the final sample established, bibliometric analyses were conducted to identify research patterns and trends. Figure 8 illustrates the temporal distribution of the total number of publications and total citations per year. There is a clear upward trend in the total number of publications, with notable increases in 2020 and 2023. Regarding citations, despite some fluctuation, peaks in 2014, 2017, and 2020 suggest that publications from these years had a significant impact on the literature.

To better understand the citation trends, Figure 9 delineates the most-cited papers

Tabela 4 – Quality assessment

Nr	Question
1	Is the methodology for validating demand forecasts robust and well-described?
2	Are the techniques used explainable and easily interpretable?
3	Is there a clear explanation of how demand forecasts are generated by these tools?
4	Are the data collection methods described transparently and in detail?
5	Are the results presented clearly and understandably, allowing assessment of the tools' effectiveness?
6	Do the reported results appear to be influenced by the authors' interests?
7	Is there a critical analysis of results in relation to existing literature?
8	Are the practical implications for professionals and organizations discussed?

Figura 7 – Quality Assessment Heatmap



within the sample. Notably, the works of Lee, Kim et al. (2014) and Goodwin, Dyussekeneva e Meeran (2013) contribute significantly to the initial sharp rise in citations. Both papers address diffusion-based methods; however, Lee, Kim et al. (2014) also introduce a hybrid approach incorporating Artificial Intelligence methods. More recently, the significant spike in 2020 is attributed to the papers by Steenbergen e Mes (2020) and Ekambaram et al.

Figura 8 – Publications and Citations per Year

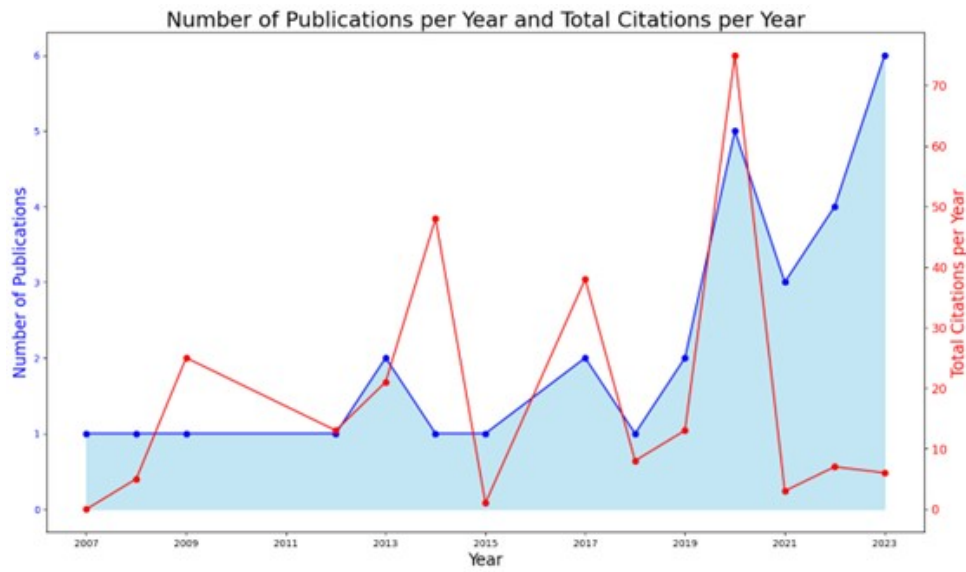
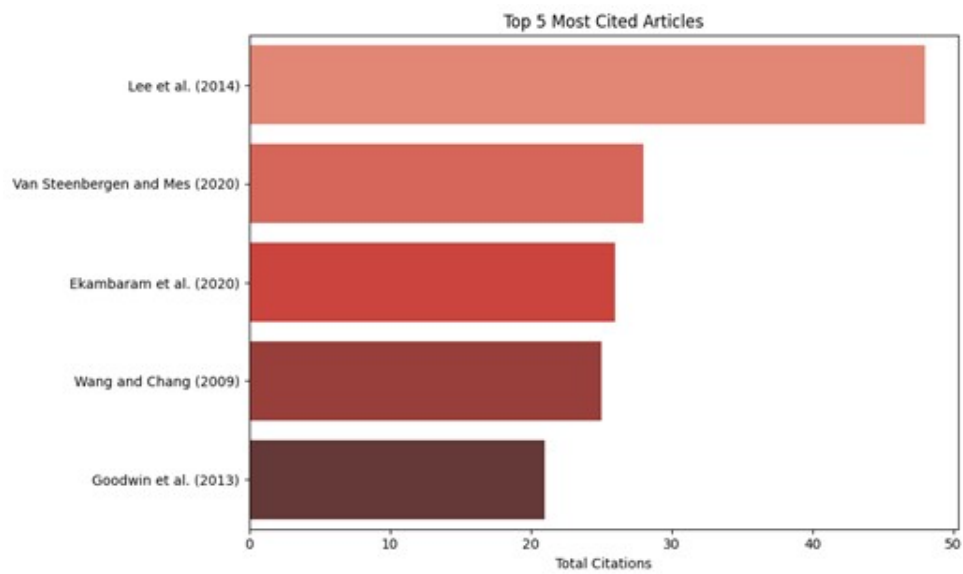


Figura 9 – Most Cited Articles

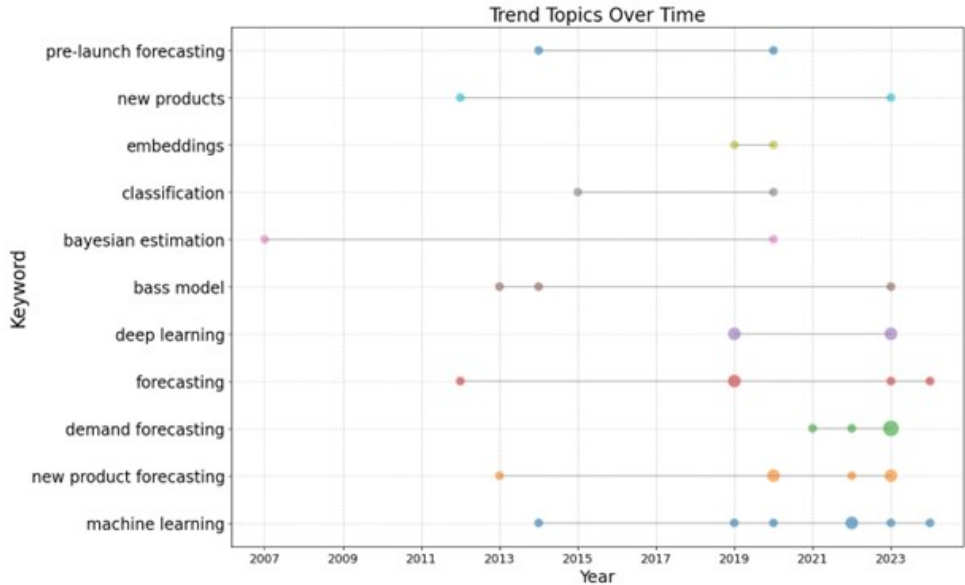


(2020), which stand out for their innovative approaches based on Artificial Intelligence.

Examining the temporal distribution of the most-cited keywords provides valuable insights into emerging trends and research focus areas. Figure 10 illustrates the keywords that appear most frequently in the studies over time, with the frequency of occurrence indicated by the size of the bubbles. This visualization reveals a significant increase in the prevalence of terms such as "deep learning" and "machine learning" in recent years. This trend underscores a growing emphasis on Artificial Intelligence techniques for forecasting new product demand, owing to their ability to model diverse scenarios with enhanced accuracy. Conversely, the term "bass model" exhibits less frequent and sporadic occurrences, reflecting a shift from traditional techniques in favor of more advanced, AI-based approaches. This change highlights the evolving landscape of forecasting methodologies and the

increasing adoption of sophisticated technologies to address the complexities of new product demand forecasting.

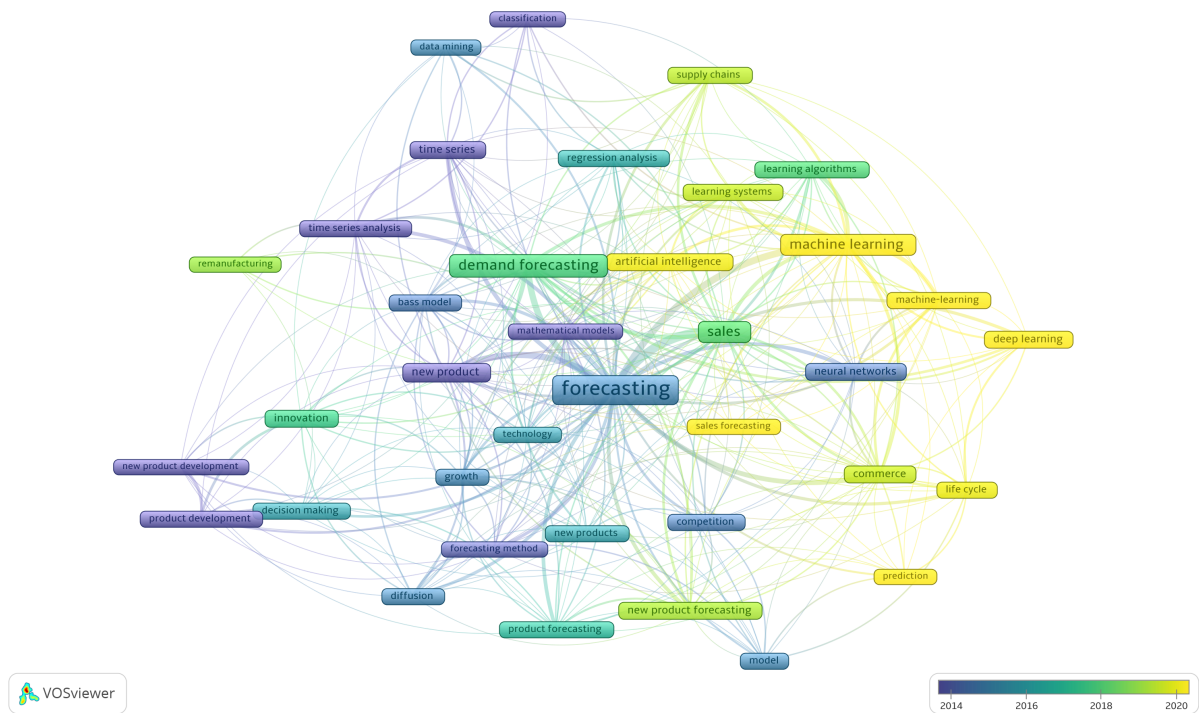
Figura 10 – Trending Topics



To complement the analysis of trending topics in this study, Figure 11 presents a graph illustrating the co-occurrence of keywords identified within the sample. This graph was generated using the VOSviewer software (ECK; WALTMAN, 2014), which organizes keywords into five distinct clusters, each represented by a different color along a temporal scale, ranging from earlier to more recent years. The color coding allows a visual representation of how certain topics have evolved: purple nodes represent keywords that were more relevant in earlier periods. In contrast, yellow nodes highlight terms that have gained prominence in recent years.

In the graph, the term "forecasting" occupies a central and highly connected position, underscoring its importance across various studies. The yellow cluster draws attention to the most recently applied techniques in forecasting demand for new products, with a particular emphasis on advancements in artificial intelligence, machine learning, and deep learning. These modern approaches have become increasingly significant in recent years. On the other hand, earlier techniques, such as diffusion models and time series analysis, are primarily represented in the purple clusters, signifying their prevalence in earlier periods of study. Additionally, terms like "competition, growth," and "decision making" are prominently featured, reflecting the critical intersection of forecasting with strategic business decisions. These terms indicate the broader implications of demand forecasting in shaping competitive strategies and guiding growth trajectories in the marketplace. Overall, this figure not only visualizes the temporal progression of forecasting methodologies but also highlights the growing integration of AI-driven techniques into demand forecasting.

Figura 11 – Overlay Visualization of Most Frequent Terms

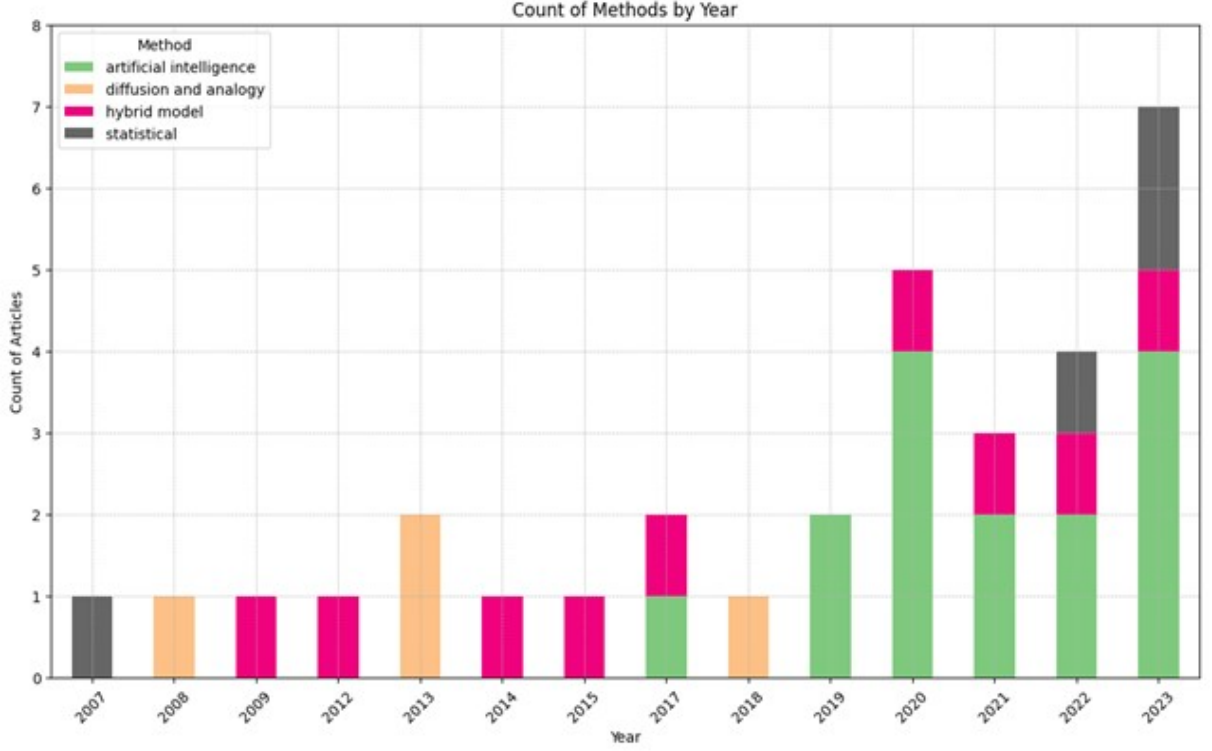


4.4 Discussion

The sample of documents included in this review, after thorough analysis, was categorized into four main groups based on the method used. Given that the goal of this review is to assess the impact of Artificial Intelligence on forecasting new product demand, it is necessary to evaluate the application of various methods in different scenarios, each proposing different solutions to problems. In this context, the first group consists of documents employing methods based on diffusion and analogy. This group represents a transition from purely judgment-based methods to quantitative approaches, establishing an intermediate state between these two extremes.

The second group encompasses documents that use statistical methods as the core of the solutions proposed by the authors. Hybrid approaches form another group, where authors propose solutions by combining different techniques such as Bass Diffusion with Machine Learning or Statistical and Computational methods. Finally, the group targeted by this study includes documents that primarily address Artificial Intelligence techniques, based on algorithms like Machine Learning, Deep Learning, and Neural Networks, among others. Figure 12 illustrates the distribution of document counts for each group by year of publication. It is observed that there has been a higher volume of documents on Artificial Intelligence in recent years, surpassing any other traditionally used techniques. Hybrid models appear as the second most frequently used technique, demonstrating their versatility in addressing forecasting problems.

Figura 12 – Count of Methods by Year



4.4.1 Diffusion and Analogy

Diffusion studies analyze the temporal evolution of initial purchases of a new product within a population (SULTAN; FARLEY; LEHMANN, 1990). One of the most widely utilized diffusion methods is the Bass model (BASS, 1969), which describes sales and adoption patterns. This approach posits that diffusion patterns can be modeled through two parameters: Innovators, who are the first to adopt the new product, and imitators, who purchase the product after coming into contact with existing users (MASSIANI; GOHS, 2015). The Bass model is represented by the following differential equation:

$$\frac{dY_t}{dt} = p(m - Y_t) + \frac{qY_t}{m}(m - Y_t) \quad (4.1)$$

where m represents the market saturation level, Y_t represents the cumulative number of adopters at time t , p is the coefficient of innovation, and q is the coefficient of imitation. Based on the Bass model, numerous other diffusion-based models have emerged. Zeng e Chen (2013) proposes an innovative approach that combines the Gompertz Curve, commonly used to model the various phases of the product life cycle, with Ant Colony Optimization to find the optimal production plan by minimizing total costs. This integration enables accurate prediction of the different stages of the life cycle of creative products, which typically lack historical sales data, and facilitates the development of an efficient production plan. The production quantities are adjusted dynamically based on

the life cycle phase of the product, with increased production during the introduction phase, followed by adjustments as the product moves through maturity and towards decline. Despite its promising results, the authors acknowledge that the methodology lacks rigorous theoretical validation, and the analysis may be prone to inaccuracies due to the inherent complexity and unpredictability of creative product markets. Similarly, Munakata e Tezuka (2008) introduces a model that allows manufacturers to make timely adjustments to production schedules and inventory levels. The proposed approach, Prop4, is specifically designed to enhance forecasting accuracy immediately after the launch of a new product, even when limited calibration data is available. This model integrates exponential and logistic elements, enabling it to adapt to various market behaviors, whether characterized by rapid initial growth or more gradual adoption patterns. By capturing these nuances early in the product's life cycle, Prop4 helps manufacturers make informed decisions on whether to continue, adjust, or halt production, ultimately minimizing risks associated with excess inventory or stockouts.

The challenges in accurately predicting sales of new electronic products were thoroughly examined by Goodwin, Dyussekeneva e Meeran (2013). The study provides a comprehensive comparison of various analogy-based forecasting methods, considering a range of factors such as the threat of substitute products, specific product characteristics, market saturation levels, and the timing of the product launch. The results reveal that forecasting sales using analogies is fraught with difficulties, as all methods tested exhibited high absolute percentage errors, underscoring the inherent unpredictability of new product markets. Despite these challenges, the study demonstrates that using multiple analogies improves forecast accuracy by averaging individual anomalies and providing a more balanced representation of potential sales patterns. However, the incremental benefit of including more than five analogies is minimal, indicating that an optimal number of analogies exists beyond which additional ones contribute little to enhancing forecast performance. Lee, Choi e Sohn (2018) developed a diffusion model that integrates patent citation data and web search traffic to forecast the sales of new technology products, using data from hybrid cars and industrial robots. The study highlights web search traffic as a crucial indicator of consumer interest, particularly for short-term demand forecasting, as it captures the evolving awareness and curiosity of potential customers. Additionally, patent citations indicate technology diffusion and market trends. This approach integrates consumer interest and technological development, enhancing strategic decision-making in dynamic markets.

Tabela 5 – Diffusion and Analogy models

Reference	Method	Evaluation Metrics	Strengths	Application
(ZENG; CHEN, 2013)	Gompertz curve and ACO	Comparison of results	The integration of life cycle modeling and optimization techniques to develop a dynamic production plan specifically tailored for products with unpredictable market behavior and short life cycles	Smartphone industry
(MUNAKATA; TEZUKA, 2008)	Prop4	MAPE	A model that enables timely production adjustments and improves inventory management	Cosmetic industry
(GOODWIN; DYUSSEKENEVA; MEERAN, 2013)	Bass model	MMAPE	The systematic evaluation of multiple analogy-based forecasting methods	Electronic products
(LEE; CHOI; SOHN, 2018)	Bass model	MAPE	The integration of patent citations and web search traffic into the diffusion model to captures both technological advancement and consumer interest	Hybrid electric vehicle and Industrial robots

4.4.2 Statistical

Traditional statistical methods for demand forecasting involve time series analysis and modeling using historical sales data. Therefore, they are not the most suitable for new product scenarios due to the lack of sufficient data. Consequently, some authors present robust statistical approaches to improve forecast accuracy. Marcek (2007) focuses on using Bayesian methods by utilizing ten months of purchase history data for lightning rods, thus not addressing the issue of lacking historical data. Bayesian methods have proven advantageous for forecasting time series with minimal observations. This technique enhances forecast accuracy by providing a framework that integrates prior and posterior estimates, along with double smoothing techniques.

The Grey Model is a forecasting technique designed for situations where data is sparse or incomplete, making it particularly useful for short-term time series analysis. In this review, two studies explore this method in detail. Li e Huang (2022) presents the Boxplot-Based Fractional Grey Model, which enhances the traditional Grey Model by incorporating a fractional calculus approach combined with boxplot analysis. This integration allows for more precise coefficient estimation and improved forecasting accuracy. The BP-FGM is especially effective in rapidly evolving industries, such as semiconductors and displays, where historical data is limited. By merging statistical visualization tools with advanced Grey System theory, this approach provides a more robust framework for demand forecasting in dynamic market environments.. In a parallel effort, Zeng, Hui et al. (2023) introduce a novel variable-structure grey prediction model (TDGM(1, 1, r, ξ)) optimized using particle swarm optimization to forecast NEV sales in China. This model expands the accumulating operator to the entire set of real numbers, significantly improving its adaptability and prediction accuracy, especially for small sample sizes and uncertain data. By incorporating a grey buffer operator for data preprocessing, the model effectively mitigates data volatility, leading to more reliable forecasts than traditional models. These advancements underscore the potential of grey models in enhancing short-term demand forecasts by integrating advanced statistical methods and optimization algorithms.

By leveraging traditional statistical methods innovatively, Elalem, Maier e Seifert (2023) present a comprehensive framework that integrates advanced techniques such as time series clustering, data augmentation, and traditional statistical modeling (ARIMAX) with sophisticated deep neural networks, including LSTM, GRUs, and CNNs. The framework provides a robust approach for forecasting sales of new products with short life cycles, even when historical data is limited. The methodology involves first clustering similar products based on historical sales patterns to identify comparable life cycles, followed by assigning new products to these clusters using quantitative measures. This allows the model to use relevant past data to improve forecasting accuracy.

Tabela 6 – Statistical models

Reference	Method	Evaluation Metrics	Strengths	Application
(LI; HUANG, 2022)	BP-FGM	MAPE	The integration of boxplot analysis with a fractional grey model, which optimizes coefficient estimation and enhances forecast accuracy	Electronic components
(ZENG; HUI et al., 2023)	Variable-structure grey model	MRPPE and MRSPE	A novel grey model for forecasting NEV sales in China is developed through the implementation of a grey buffer operator	New Energy Vehicles
(ELALEM; MAIER; SEI-FERT, 2023)	ARIMAX, LSTM, GRU, and CNN	SAE and MASE	Its use of time series clustering to identify similar product patterns and data augmentation to enhance limited datasets	Electronic products
(MARCEK, 2007)	Bayesian estimation	Comparison between actual and forecasted values	The integration of Bayesian parameter estimation with causal regression models	Electronic components

The following formula represents the Euclidean distance calculation used to measure the similarity between the sales patterns of each product pair i and j :

$$ED(\tilde{D}^{a,i}, \tilde{D}^{a,j}) = \sqrt{\sum_{t=0}^n (\tilde{D}_t^{a,i} - \tilde{D}_t^{a,j})^2} \quad (4.2)$$

where $(\tilde{D}_t^{a,i}, \tilde{D}_t^{a,j})$ is the pair of smoothed sales at time t , and n is the entire length of the time series. Data augmentation is then applied to enhance the limited available data, generating additional data points to ensure the models are well-trained and can capture the underlying sales dynamics. The empirical results indicate that while ARIMAX achieves lower mean absolute error, DNNs demonstrate superior resilience to data noise and variability. This robustness suggests that DNNs are particularly well-suited for scenarios where demand is highly volatile.

In summary, while traditional statistical methods have a limitation when forecasting demand for new products due to the scarcity of historical sales data, some advanced approaches, such as Bayesian and Grey Models, offer viable solutions. By incorporating prior knowledge, adapting to sparse data, and integrating sophisticated data processing and optimization algorithms, these methods can enhance prediction accuracy and adapt to different scenarios. Table 6 presents the statistical methods utilized in this study.

4.4.3 Hybrid Models

Hybrid models attempt to leverage the positive aspects of different approaches to overcome the difficulties encountered in forecasting. Consequently, this category represents 26.67% of the total sample of papers included in this review. Table 7 presents the hybrid methods employed in the study.

Three papers employ the Bass diffusion model in combination with other methods. Lee, Kim et al. (2014) employed the Bass model to describe the product diffusion process, enhancing it by integrating machine learning algorithms to predict the model's parameter accurately. The authors propose a comprehensive approach by constructing two distinct databases: one capturing product attributes and another representing product diffusion characteristics. These databases serve as the foundational inputs and outputs for six different machine learning algorithms —MLR, KNN, ANN, SVR, CART, and GPR— used to estimate the parameters of the Bass model. A notable aspect of their approach is the expert judgment incorporation while creating the product attribute database. This step is essential, as it draws upon the expertise of industry managers, ensuring that the model reflects practical, real-world insights. While the forecasting model uses these expert-assessed attributes as inputs for parameter prediction, it minimizes human intervention in later stages, relying on the computational power of machine learning to improve accuracy and objectivity throughout the forecasting process. The expert knowledge integration in

the initial phase thus enhances the model’s reliability while maintaining a data-driven approach in subsequent steps.

Ramírez-Hassan e Montoya-Blandón (2020) propose a Bayesian estimation procedure for the Generalized Bass Model. This approach allows for pre-launch forecasts by drawing analogies with similar previous markets and incorporating marketing efforts into the model. This addition is incorporated as a multiplicative term on the right-hand side of the standard representation of the Bass model:

$$\frac{f(t)}{1 - F(t)} = \left[p + \frac{q}{m} Y(t) \right] x(t), \quad (4.3)$$

where $x(t)$ is the market effort:

$$x(t) = 1 + \beta_1 \frac{P(t) - P(t-1)}{P(t-1)} + \beta_2 \frac{\max\{0, A(t) - A(t-1)\}}{A(t-1)}, \quad (4.4)$$

where $P(t)$ and $A(t)$ are the price and the advertising, respectively.

The authors conducted several simulation exercises and applied their method to forecast sales of air conditioners, BlackBerry devices, and compressed natural gas. Yan e Hu (2023) emphasize the importance of word-of-mouth within and across products in the diffusion of new products and demand forecasting. In their study, they use ABMS and the Bass model to improve demand forecasting and production capacity adjustment strategies. The Bass model, which traditionally forecasts product adoption based on innovation and imitation effects, is extended to include within-product and cross-product WOM influences, acknowledging that consumer decisions are affected not only by communication about the product in question but also by experiences with other products from the same manufacturer. The ABMS approach simulates individual consumer behaviors and interactions, allowing for a more granular analysis of market diffusion dynamics. They propose three production capacity adjustment strategies (cautious, proactive, and moderate) through simulation scenarios with varying parameters, such as advertising intensity, WOM levels, and capacity adjustment cycles.

Four other studies incorporate statistical approaches into their hybrid models. Lee, Lee e Lee (2012) focus on demand forecasting by utilizing consumer reservation price data, which represents the maximum price a consumer is willing to pay, in combination with Bayesian updating. The proposed model begins by estimating consumer adoption timing based on reservation price data collected through surveys. Forecasts are continuously updated using actual sales data through a Bayesian framework, allowing for more accurate and refined predictions. This dynamic updating process makes the model particularly effective during the early stages of a product’s life cycle, where data is typically limited and uncertainty is high. Hryniewicz e Kaczmarek (2015) utilize an approach that integrates Bayesian autoregressive forecasting with soft computing techniques, such as linguistic

summarization and supervised learning. In this method, Bayesian autoregressive forecasting is used to update predictions based on the posterior distribution of the parameters, taking into account prior knowledge (derived from expert opinion or data mining) and newly observed data. The formula is structured as follows:

$$p(\theta_M|y, M) = \frac{p(\theta_M|M) \cdot p(y|\theta_M, M)}{p(y|M)} \quad (4.5)$$

Its components denote: $p(\theta_M|y, M)$ is the posterior distribution of the parameters given the observed data and the model, $p(\theta_M|M)$ is the prior distribution, which incorporates expert knowledge or prior information, $p(y|\theta_M, M)$ is the likelihood of the observed data given the parameters and the model, and $p(y|M)$ is the marginal likelihood, or the evidence, of the observed data under the model. Using MCMC methods, the approach generates pseudo-random sequences to estimate posterior moments, improving both the interpretability and reliability of the forecasts.

Chen et al. (2022) propose a two-layer model for forecasting the demand for fashion products, effectively addressing the challenge of censored demand in physical stores. The first layer uses linear regression to estimate demand, while the second layer models sales based on the estimated demand and inventory levels. To improve accuracy, the model employs the gradient-boosting decision tree method for feature selection and uses a genetic algorithm to refine parameter estimation within each product cluster. Additionally, introducing two key metrics—average and marginal conversion rates—provides managers with valuable insights into product competitiveness and inventory optimization. Similarly, Dai e Huang (2021) presents a sales forecasting method for new products that rely on similarity measures, consistency checks, and random feature search methods. Their approach utilizes a weighted Euclidean similarity measurement to identify products most similar to the new product, though it focuses mainly on product characteristics. A consistency test is then applied to ensure that the sales of these similar products align closely with the sales expectations of the new product. If the sales patterns meet the criteria, the sales forecast is generated by calculating a weighted average of the initial sales of similar products. If the consistency test fails, the model performs a random search for new feature sets until the sales forecast criteria are met or a predetermined threshold is reached.

Wang e Chang (2009) introduced a modified diffusion model that integrates a HGA to improve parameter estimation in the Bass model. This approach incorporates an average price factor, which allows the model to capture the influence of pricing dynamics across different product generations, enhancing the accuracy of multi-product demand forecasting. The model was validated using two distinct sales datasets. Initially,

the authors employed nonlinear least squares to derive preliminary estimates for the parameters. Subsequently, the HGA was applied to refine these estimates and achieve a more comprehensive parameter optimization. To evaluate the robustness and precision of the parameter estimates, the authors used MCMC simulations. Incorporating the average price factor into the diffusion model enables a more nuanced understanding of how price variations affect the market potential of each product generation. Concluding the category of hybrid models, the newsvendor problem under complete uncertainty for innovative products is addressed by (GASPARS-WIELOCH, 2017). The proposed methodology involves a new scenario-based decision rule that combines aspects of the Hurwicz and Bayes decision rules, considering the decision maker's risk attitude and the dispersion of rewards associated with different order quantities.

Tabela 7 – Hybrid methods

Reference	Method	Evaluation Metrics	Strengths	Application
(LEE; KIM et al., 2014)	Bass and MLR, KNN, ANN, SVR, CART, GPR	MAE and RMSE	The integration of the Bass model with ML, along with the use of expert judgment in the creation of the product attribute database	Eletronic products
(RAMÍREZ-HASSAN; MONTÓYA-BLANDÓN, 2020)	GBM and Bayesian estimation	MSE, MAE, RMSE	A comprehensive validation through both simulation exercises and real-world applications across different product types	Eletronic products and Natural gas
(YAN; HU, 2023)	Bass and ABMS	NPV and LCN	The integration of production capacity adjustment, which dynamically adapts production levels according to demand forecasts	Manufacturing industry
(LEE; LEE; LEE, 2012)	Reservation price and Bayesian updating	MAPE and BIC	The use of consumer reservation price as a central feature to predict adoption timing for new products	Broadband internet services
(HRYNIEWICZ; KACZMAREK, 2015)	Bayesian autoregressive forecasting, soft computing and SVM	SSE	The integration of linguistic summaries and supervised learning in the forecasting process, along with the application of Bayesian inference for handling short time series	Simulation data
(CHEN et al., 2022)	Linear Regression, GBDT and Genetic algorithm	MAE and MAPE	The two-layer model, combined with the introduction of innovative metrics	Fashion industry
(DAI; HUANG, 2021)	similarity measures, consistency checks, and random feature search	RMSPE	The flexibility of the model allows it to adapt to different product categories.	Car sales
(WANG; CHANG, 2009)	Modified diffusion model	MSE and R^2	The incorporation of an average price factor into the modified diffusion model	Eletronic products
(GASPARS-WIELOCH, 2017)	hybrid of Hurwicz and Bayes decision rules	2-criteria (H+B) rule	It integrates decision-makers' risk preferences directly into the forecasting model	Fashion and Food industry

4.4.4 Artificial Intelligence

With a range of distinct approaches and innovative solutions, artificial intelligence-based methods stand out for their versatility, accuracy, and ability to handle complex patterns and nonlinear relationships. Therefore, the main artificial intelligence approaches for demand forecasting of new products will be presented below. The models are classified into Machine Learning or Deep Learning approaches. Table 8 presents the methods used in the studies.

4.4.4.1 Machine Learning Models

Some studies in the sample use KNN techniques directly or indirectly. This algorithm classifies a data point based on the majority of its nearest neighbors. Kalla, Murikinjeri e Abbaiah (2020) focused on identifying geographically similar products with sufficient and consistent sales history using KNN. A similarity calculation using Euclidean distance and exponential weighting prioritizes closer products:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^n (x_{ik} - x_{jk})^2} \quad (4.6)$$

where x_{ik} and x_{jk} are the coordinates of the points on their respective axes. Traditional ML then predicts demand for Geo-Prods in the sufficient history cluster, and the weighted average forecast aggregates the predictions.

The study by Esmeli, Mohasseb e Bader-El-Den (2020) utilizes KNN, DT, and Bagging Classifier to predict consumer purchase behavior by analyzing platform and operating system characteristics. In this model, KNN classifies new user data based on the behavior of similar past sessions, aiding in the identification of purchase intent. The Decision Tree, a rule-based algorithm, recursively splits data according to the most informative features, identifying key factors—such as session duration and operating system—that influence purchase decisions. The Bagging Classifier enhances the model’s robustness by training multiple decision trees on different data samples and combining their predictions, thereby reducing errors and improving overall accuracy. The data analysis includes the distribution of user-website interactions across weekdays, hours, operating systems, and platform types.

Decision tree-based methods are also present in the sample. Zahmatkesh et al. (2021) and Smirnov e Sudakov (2021) propose solutions using Gradient Boosting to forecast demand in short life cycle industries and online stores, respectively. GB is one of the most effective methods for solving regression tasks, particularly in forecasting demand for new products. By combining multiple ‘base’ classifiers, this powerful technique creates a committee, which typically achieves superior performance compared to any single base classifier (BISHOP, 2006).

Algorithm 1 Gradient Tree Boosting for Regression

```
1: Initialize  $f_0 = \arg \min_{\gamma} \sum_{i=1}^N L(y_i, \gamma)$ .
2: for  $m = 1$  to  $M$  do
3:   for  $i = 1, 2, \dots, N$  do
4:      $r_{im} = - \left[ \frac{\partial L(y_i, f(x_i))}{\partial f(x_i)} \right]_{f=f_{m-1}}$ 
5:   end for
6:   Fit a regression tree to the targets  $r_{im}$ , giving terminal regions  $R_{jm}$ , for  $j = 1, 2, \dots, J_m$ .
7:   for  $j = 1, 2, \dots, J_m$  do
8:      $\gamma_{jm} = \arg \min_{\gamma} \sum_{x_i \in R_{jm}} L(y_i, f_{m-1}(x_i) + \gamma)$ 
9:   end for
10:  Update  $f_m(x) = f_{m-1}(x) + \sum_{j=1}^{J_m} \gamma_{jm} I(x \in R_{jm})$ .
11: end for
12: Output  $\hat{f}(x) = f_M(x)$ .
```

Algorithm 1 outlines the working mechanism of gradient tree boosting. The algorithm initializes f_0 to minimize the loss function L . Then, a loop runs for M iterations, where a residual model (r_{im}) is adjusted, representing the negative gradient of the loss function. In each iteration, a regression tree is fitted to the residuals, and optimal values are calculated to minimize the loss in each terminal region R_{jm} . The model is then updated by adding the adjustment to the previous prediction $f_{m-1}(x)$. After completing the iterations, the final prediction ($f_M(x)$) is obtained, with accuracy improving progressively.

Architectures designed to model time series are also used. Rodriguez-Aguilar, Marmolejo-Saucedo e Garcia-Llamas (2024) combines classical forecasting methods, such as ARIMA models (presented in Eq 4.7), with more recent ML methodologies like LSTM and SVM. The system automatically selects the optimal forecasting model for each product family and period, with a specific focus on food products. ARIMA models serve as a baseline due to their simplicity and popularity, offering a foundation for comparison with more advanced models like LSTM-RNN and SVM.

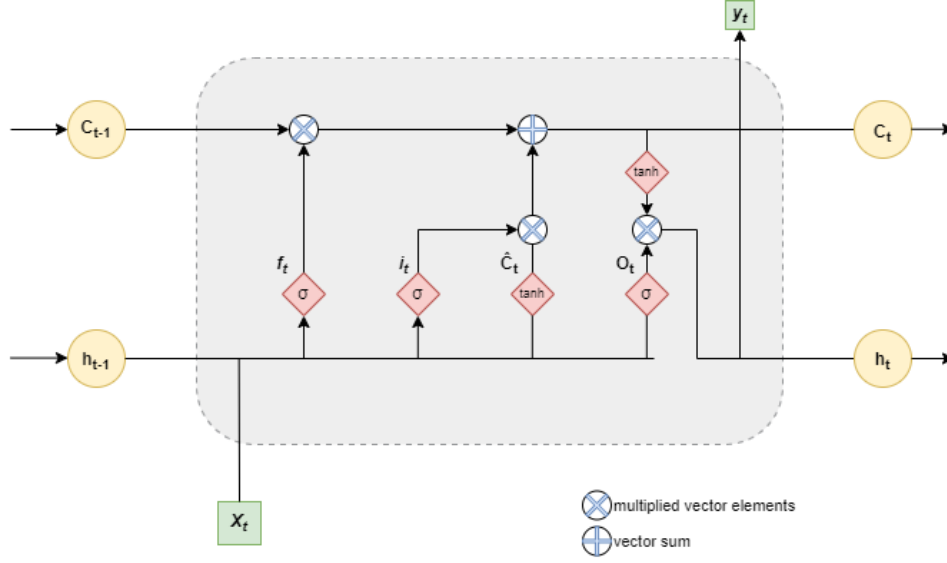
$$Y'_t = c + \phi_1 Y'_{t-1} + \dots + \phi_p Y'_{t-p} + \theta_1 e_{t-1} + \dots + \theta_q e_{t-q} + e_t \quad (4.7)$$

It combines autoregressive terms (ϕ) and moving average terms (θ).

The LSTM neural network outperformed for most products due to its ability to capture non-linear relationships and controlling the flow of information to preserve important time-based features for accurate forecasting. Fig. 13 presents the cell structure of LSTM.

The flow of information is controlled through three main gates: the forget gate (f_t), the input gate (i_t), and the output gate (O_t). The forget gate updates the cell state

Figura 13 – Structure of LSTM



(C_t) by discarding irrelevant information from the previous state (C_{t-1}). The input gate determines which new information (X_t) will be incorporated into the updated cell state. Finally, the output gate decides which information from the new cell state will be passed to the hidden state using the sigmoid function (σ). A hyperbolic tangent function ($\tanh$) is employed to create a candidate memory ($\tilde{C}_t$). This allows the LSTM to retain, forget, and update information at different points in time.

Ma et al. (2023) utilize a similar strategy, combining SARIMA, LSTM, and BP-neural networks. The study highlights the importance of accurate demand forecasting in the NEV sector to drive development and sustainability. The ARIMA model is widely used for univariate time series prediction but lacks support for seasonality. To address this, the SARIMA model extends ARIMA to handle trends and seasonal components. The SARIMA model is expressed as:

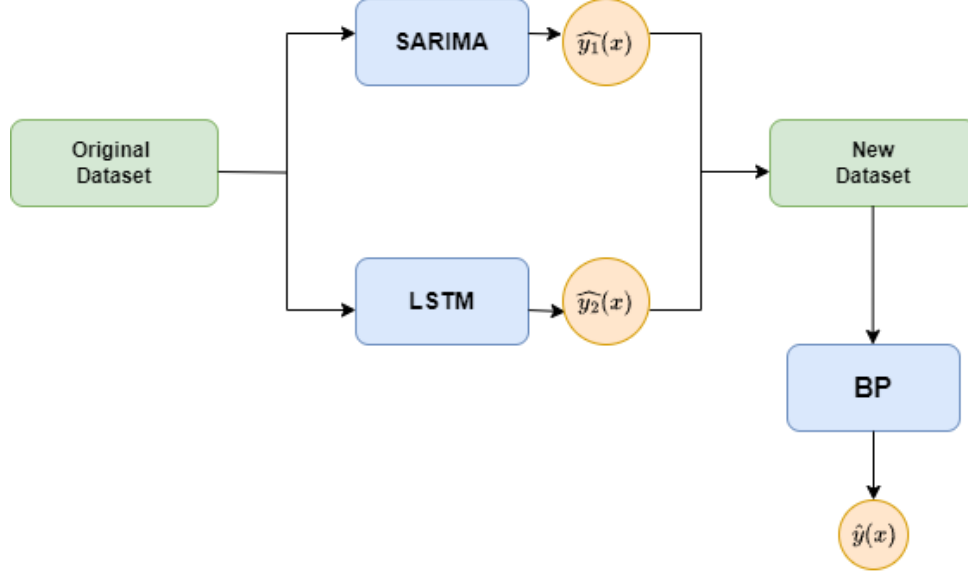
$$\text{SARIMA}(p, d, q) \times (P, D, Q)_s \quad (4.8)$$

p , d , and q represent the autoregressive order, trend difference order, and moving average order, respectively, as in ARIMA. The seasonal factors are P for seasonal autoregressive order, D for seasonal difference order, Q for seasonal moving average order, and s for the length of the seasonal cycle.

Considering that research subject can be influenced by various factors, using distinct models emphasizing their specific characteristics enhances the robustness of the forecast. With this in mind, the authors applied the ensemble learning approach, specifically the stacking method, to integrate the different models. Fig. 14 illustrates the flowchart of the model used by the authors. In this case, the samples were first processed by individual models (SARIMA and LSTM), and their results were then combined into a new dataset.

This new dataset was used as input to train a second model, known as the "secondary learner," which generated a better-fitted model combination.

Figura 14 – Flowchart of the model by (MA et al., 2023)



Other authors have also introduced innovative approaches based on machine learning. Huang e Liu (2017) developed a two-stage retail forecasting system for new clothing products. In the first stage, the model estimates demand using original sales data while accounting for stock-out scenarios. This step is crucial, as actual sales may not accurately represent true demand under such circumstances. In the second stage, the ANFIS is employed to forecast demand. This method integrates ANN with fuzzy logic, combining the learning capabilities of ANN with the interpretability of fuzzy systems. The system allows for the consideration of various factors that influence demand, including price, promotion levels, and size preferences, among others. The ANFIS-based approach demonstrated an effective ability to handle both qualitative and quantitative variables, resulting in improved overall forecasting accuracy.

Steenbergen e Mes (2020) introduce a novel method known as DemandForest. This ML model leverages historical sales data of previously launched products and the characteristics of both existing and new products to generate pre-launch forecasts, with a particular focus on supporting inventory management decisions. The process begins by clustering existing products based on their demand profiles using the K-means algorithm, which helps identify distinct demand patterns that new products may follow. Following the clustering, an RF algorithm classifies the new product into one of the existing clusters based on its product features. Subsequently, the QRF algorithm is applied to estimate the total demand for the new product while quantifying the uncertainty of the prediction by providing prediction intervals. This feature aids inventory management by enabling companies to prepare for fluctuating demand levels. The final forecast for each period is

produced by combining the total demand estimate with the predicted demand profile.

Finally, McRae, Nie e Dube (2022) implemented 18 different ML models to predict demand for yogurt products at two different levels: the market level and the store level. The study does not face the issue of insufficient data as it uses raw data from a loyalty program. At the market level, the prediction focuses on estimating the total demand for yogurt products across the entire market. In this case, the dataset combines data from all stores and aggregates sales information. Market-level models aim to predict how much of a specific product will be sold across the entire region covered by the stores. RF model performed best at this level. At the store level, the focus is on predicting demand for specific products at each individual store. The difficulty is that demand can vary between stores based on local factors. For this level, the best-performing model was the Light Gradient Boosting Machine.

To understand the impact of individual features on the predictions, the authors used SHAP. This method helps explain the contribution of each feature to the model's prediction. At the market level, SHAP values revealed that the most important features were related to product type, the number of stores where the product was available, and marketing activities. At the store level, SHAP indicated that local features like population density and store size had the most significant impact.

4.4.4.2 Deep Learning Models

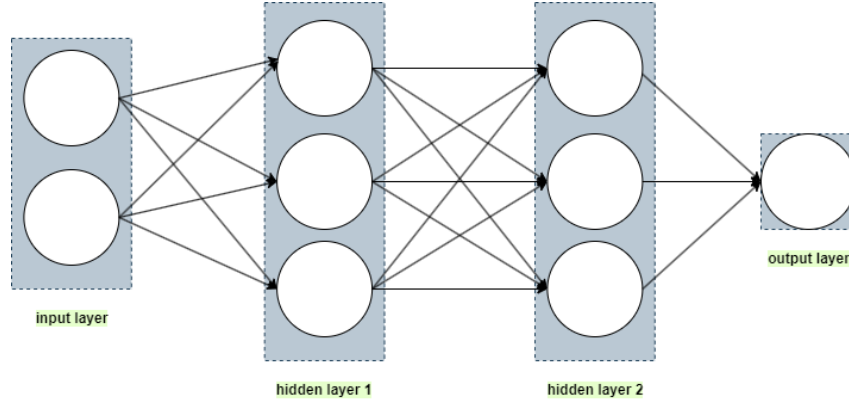
This AI subcategory utilizes artificial neural networks with multiple hidden layers to effectively model complex and non-linear patterns in data, enabling the capture of intricate relationships that are often difficult to detect with simpler models. Lin et al. (2023) introduced the KEM-QRGBT model for forecasting the demand for new electronic products, addressing the challenge of limited historical data. The model predicts future life cycles by analyzing the similarity of older products' life cycle curves and estimates demand at different stages. It operates in four main steps, beginning with clustering the life cycles of older products using the K-means algorithm based on Euclidean distance. Next, the MLP algorithm is trained on features of older products and their corresponding life cycles to predict the life cycle curve of new products. Additionally, the system uses Quantile Regression with GBT to predict total demand, quantifying uncertainty and forecasting demand across different intervals. Finally, by multiplying the predicted total demand by the forecasted life cycle curve, the model generates multi-period demand interval forecasts for the new product.

Giri et al. (2019) focus on forecasting sales of new women's clothing by analyzing historical sales data and product images. Their approach utilizes a backpropagation neural network to predict future sales based on a small dataset. The Inception v3 deep learning model is employed to extract feature vectors from the product images, which are then

combined with the products' historical sales data.

The final forecasting model is a multilayer perceptron (MLP), a feedforward artificial neural network consisting of three layers: an input layer, a hidden layer with 100 neurons using ReLU activation, and an output layer, as shown in Fig. 15. This model generates future sales predictions by incorporating both visual image features and historical sales data, enabling a more accurate adaptation to fashion industry market trends.

Figura 15 – MLP Workflow



Mezzogori e Zammori (2019) propose a two-step sequential prediction model. The first step involves constructing a pseudo time series for new products based on the sales of similar products from previous collections. The authors employ entity embeddings to capture complex, non-linear relationships between product features and customer preferences. In the second prediction step, an RNN processes the pseudo time series generated in the previous stage, combining it with actual order data to forecast the final sales of each product. This model was tested in an Italian fashion company. The fashion industry faces an increasing need for precise demand forecasting of new products, driven by frequent collection changes and evolving consumer purchasing patterns. Ekambaram et al. (2020) contributed to this field by proposing a multi-modal approach that combines various data types, including product images, structured attributes, and external factors like weather, holidays, and promotions. This approach utilizes an RNN to process these diverse inputs, while attention mechanisms are employed to identify the most relevant features for accurate forecasting, enhancing the model's interpretability. By integrating images, sales data, and external influences, this method provides an innovative and effective solution to the challenges of demand forecasting in cases with limited historical sales data.

A novel method for correlation analysis of tobacco products using a knowledge graph integrated with a graph neural network is proposed by Yang et al. (2023). This method constructs a knowledge graph from real-world tobacco data, including brand, sales history, and attributes, to analyze correlations between old and new tobacco products, aiding in formulating sales strategies. The GNN predicts correlations between tobacco products using semi-supervised learning methods, offering precise sales trend predictions

for new tobacco products. Fig 16 illustrates the model's training process, from data collection to the construction of knowledge graphs, which are used to generate predictions about the sales of new products. This diagram delineates the structure and data flow of the proposed method, detailing how the GNN is trained with an adjacency matrix. To calculate the correlation between different tobacco products, the authors employed cosine similarity, which compares the attribute vectors of two products and generates a numerical value representing their degree of similarity. The cosine similarity is expressed as follows:

$$\cos \theta = \frac{\sum_{i=1}^n (X_i^1 X_i^2)}{\sqrt{\sum_{i=1}^n (X_i^1)^2} \sqrt{\sum_{i=1}^n (X_i^2)^2}} \quad (4.9)$$

where X_i^1 and X_i^2 represent the N-dimensional vectors corresponding to the characteristic attributes of two different types of tobacco, respectively.

Figura 16 – Flow diagram of the semi-supervised graph neural network by (YANG et al., 2023)

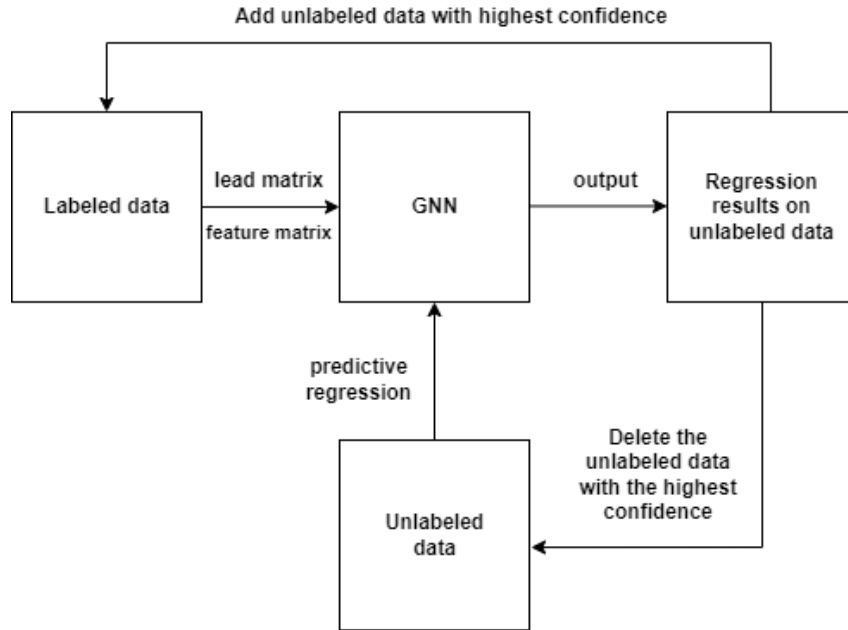


Tabela 8 – AI methods

Reference	Class	Method	Evaluation Metrics	Strengths	Application
(LIN et al., 2023)	DL	KEM-QRGBT	Calinski-Harabasz Index; Accuracy; PICIP; PINAW	A model that integrates clustering, NN, ensemble regression, featuring adaptive parameter selection and robust uncertainty quantification	Electronic products
(GIRI et al., 2019)		CNN and NNMLP	MSE; RMSE; MAE; R^2	The combination of historical sales data with visual features extracted through deep learning, while the use of an MLP model optimized by BP enhances predictive accuracy, even with a small dataset.	Fashion industry
(MEZZOGORI; ZAMMORI, 2019)		RNN	MAPE	The approach leverages entity embeddings to represent categorical variables and constructs pseudo time-series by identifying similarities with past products	Fashion industry
(EKAMBARAM et al., 2020)		KNN and RNN	MAE; wMAE; PCC	The integration of product images, attributes, and external factors using neural encoder-decoder architectures. Attention mechanisms to filter irrelevant features, and multi-modal fusion to enhance performance	Fashion industry
(YANG et al., 2023)		GNN	Cosine similarity	The application of GNN and knowledge graphs to forecast demand, while also minimizing the need for manual feature extraction, enhancing automation in the analysis process	Tobacco products
(YAMAMURA et al., 2022)		ANN	MAPE	The combination of deep learning with expert domain knowledge to predict the demand for new products	Automobile industry

Tabela 8 – (Continued)

Reference	Class	Method	Evaluation Metrics	Strengths	Application
(KALLA; MU-RIKINJERI; ABBALIAH, 2020)	ML	KNN	MAE; MAPE	The identification of similar geographical-products combinations to improve forecast accuracy	Retail
(ESMELI; MOHASSEB; BADER-EL-DEN, 2020)		KNN, DT, and BC	F-Score	The integration of multiple machine learning algorithms and the incorporation of platform and operating system features	E-commerce
(ZAHMATKESH et al., 2021)		XGBoost and GB	MAPE	Enhancement of human expert judgment in new product demand forecasting through the application of ML approaches	Fashion industry
(SMIRNOV; SUDAKOV, 2021)		GB	RMSE	Accurate demand forecasting based solely on product attributes such as price, category, description, and time-related features	E-commerce
(RODRIGUEZ-AGUILAR; MARMOLEJO-SAUCEDO; GARCIA-LLAMAS, 2024)		LSTM and SVM	RMSE	The ability to capture both linear and non-linear patterns through the integration of classical statistical models and ML. This flexible approach dynamically selects the most appropriate model based on performance metrics.	Food industry
(MA et al., 2023)		SARIMA-LSTM-BP	RMSE and MAE	The innovative combination of traditional time series analysis with ML and DL models for providing accurate forecasting	New energy vehicle
(HUANG; LIU, 2017)		ANFIS	MAPE and MSE	A hybrid technique that combines ANN and fuzzy logic	Fashion industry
(STEENBERGEN; MES, 2020)		K-means, RF and QRF	RMSE; P1CP; PINAW	Integration with inventory management, offering both demand forecast and uncertainty intervals	E-commerce; Retail; Wholesale
(MCRAE; NIE; DUBE, 2022)		RF	MAE; RMSE; MAPE	The use of loyalty program data combined with ML models	Food retail

An innovative approach that integrates managerial domain knowledge with machine learning techniques is presented by Yamamura et al. (2022). In this study, an artificial neural network with a hidden layer is utilized to predict the market share of new SUVs launched in Brazil between 2016 and 2020. The process begins with the manager using their domain expertise to identify the key product attributes that influence market performance, drawing from years of industry experience. This initial hypothesis, grounded in practical knowledge, serves as a starting point for the model. Managerial insights also guide the crucial stages of data pre-processing, ensuring that relevant variables are properly refined and considered during the neural network simulation. Throughout this process, the model captures complex, nonlinear relationships between the variables, offering deeper insights into market dynamics. The study's findings underscore the effectiveness of this hybrid approach, highlighting the critical role of collaboration between managers and data scientists in producing more accurate and reliable demand forecasts.

4.5 Results and Main Findings

To further advance towards answering the guiding research question of this study, as well as achieving objective (2) - Evaluate the performance of AI tools compared to traditional methods - this section will undertake a comprehensive comparative analysis of AI methodologies against traditional forecasting models through various lenses. While the assessment of model metrics is an essential component of this analysis, it alone does not suffice, given that each model has been implemented in distinct contexts and conditions. Therefore, this section will also explore additional evaluation criteria, including the robustness and complexity of the models, their inherent limitations, and the practical implications of their application.

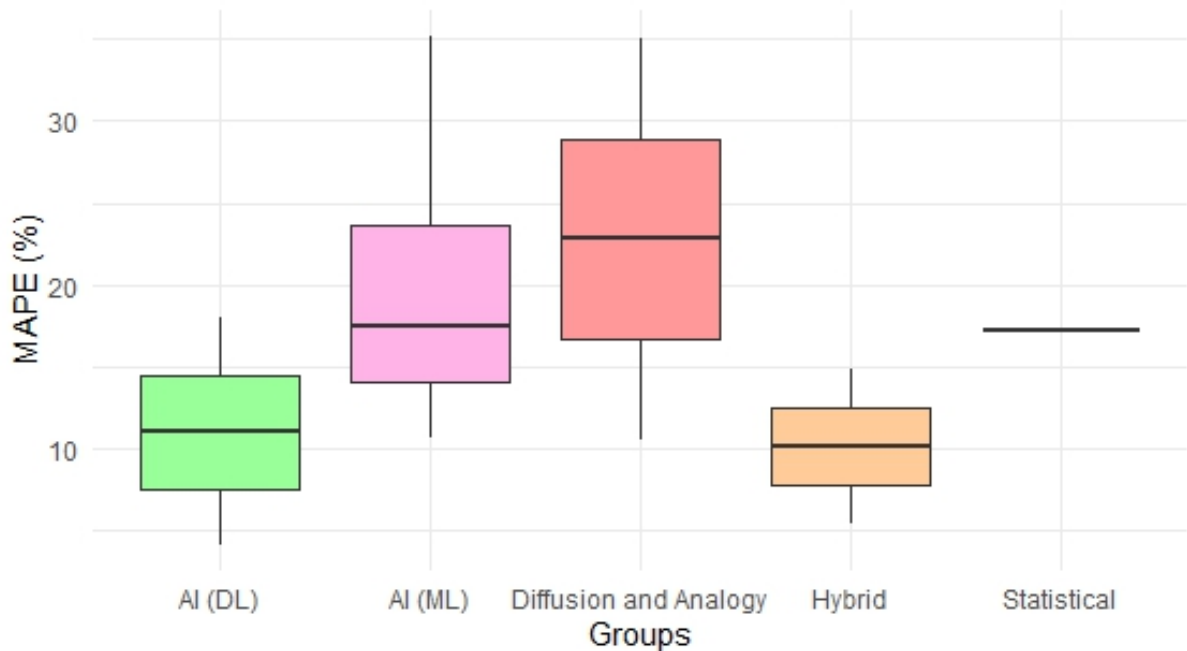
4.5.1 Performance Evaluation

The evaluation of forecasting models is a crucial step in formulating proposals, as it not only demonstrates the accuracy and reliability of the models but also provides insight into their practical applicability in real-world scenarios. Employing specific metrics enables researchers to quantify and compare different methodologies effectively, facilitating a clearer understanding of each model's strengths and weaknesses. In this study, the authors employed metrics they deemed most appropriate for assessing their respective models; consequently, significant variability exists in the metrics reported across the selected studies for the review, reflecting the diverse contexts in which these models were applied.

To facilitate a more equitable evaluation of the various methods within each forecasting group—diffusion and analogy, statistical, hybrid, and AI—the MAPE metric

was chosen for this analysis. MAPE is the most frequently utilized metric among all methodologies and stands out as the only measure that consistently appears across each of these groups. This consistency enables a more thorough comparison of performance. Additionally, it is essential to note that the authors applied their models in diverse contexts, resulting in differences in testing methods and conditions. For instance, studies within the fashion industry typically evaluated the models to predict demand for specific products, such as jackets or shirts, while research in the automotive field examined the models across various categories of vehicles. Due to these distinctions, only the results from one of these predictions were chosen for comparison, ensuring that the evaluation remains concentrated and pertinent to the broader research aims.

Figura 17 – MAPE by groups



Despite the differences between the proposed methods, which can make their comparison challenging, Figure 17 illustrates a boxplot showing the variation in MAPE across the various groups of forecasting models. Hybrid models display the lowest variability and a lower median, followed closely by DL models. In contrast, diffusion-based models have the highest median MAPE values and a larger interquartile range. The ML group presents intermediate values, with a broader range of MAPE scores compared to DL, suggesting that although ML models can be effective, their performance tends to be less consistent. Overall, this analysis indicates that AI-based and hybrid models generally achieve better MAPE whereas diffusion and analogy models demonstrate greater variability and relatively poorer accuracy.

4.5.2 Robustness and Complexity

In addition to the usual performance indicators such as MAPE, MAE, and RMSE, it is essential to consider the robustness and complexity of each method to provide a more comprehensive assessment of forecasting models. Accurate demand forecasting, in practical terms, is influenced by various factors, including the ability to implement the model and adapt to unpredictable conditions. Consequently, models that demonstrate not only high accuracy but also robustness and simplicity become significantly more relevant and applicable. This approach ensures that the proposed solutions are effective not only in ideal circumstances but also in more challenging environments.

A database was established by the authors to investigate the relationship between the complexity and robustness of each forecasting model. A scale of 1 to 5 was used to evaluate each item; values near 1 denote less robustness or complexity, while values near 5 denote the reverse. The performance of the papers in various scenarios and data sets, the addition of external variables, stability, and generalization ability were all evaluated in order to determine how resilient the papers were. The amount of parameters, model structure, requirement for modifications, simplicity of interpreting findings, and model operation were all taken into account while assessing complexity.

Figure 18 – Scatter Plot of Robustness and Complexity

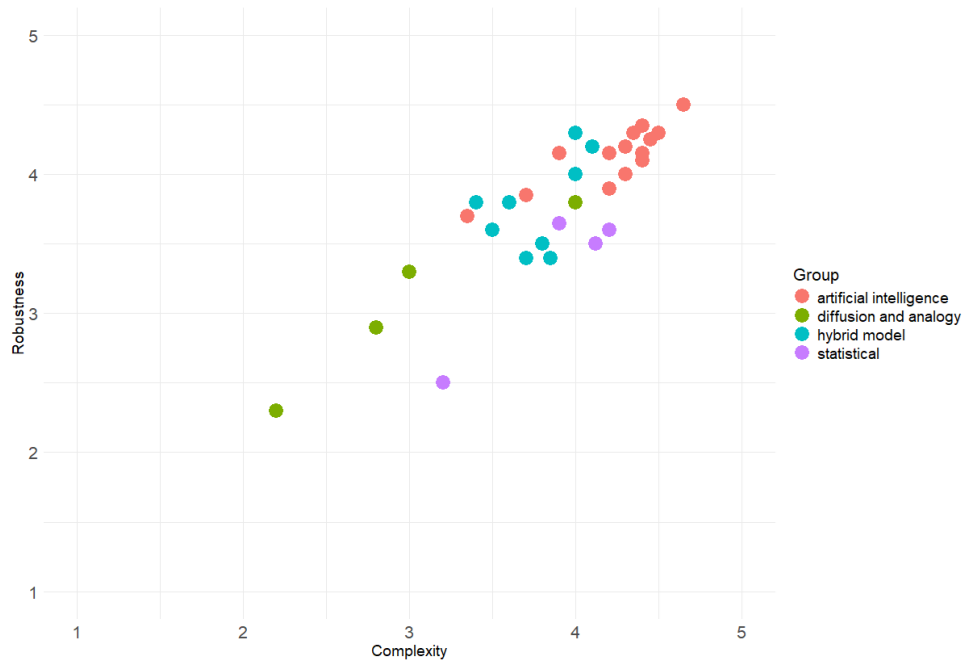


Figure 18 depicts a scatter plot, with each point representing an article from the sample under consideration. Statistical models are particularly robust within the context in which they are designed to work since they incorporate a variety of methodologies, the flexibility to adapt to scenarios, and solid procedures. However, this capacity increases with the complexity of the models, necessitating a high level of expertise for changes

and manipulations. It is also obvious that the articles selected fulfilled difficult selection standards, as seen by a sample of carefully planned studies. On the other hand, diffusion and analogy models are less difficult because they are based on simple models with few parameters. Even though the methods for estimating the parameters differ, they remain less complex. The robustness of these models increases with the addition of new variables or the combining of data from other sources.

Hybrid and artificial intelligence models are represented in the graph's upper right quadrant, demonstrating great complexity and robustness. The challenge for these methods is to create a model that is more resilient and less complex, making it feasible in practice, more widely used by decision-makers, and easier to modify for improved accuracy. By leveraging different data sources, combining innovative methodologies, focusing on adaptability, and involving different agents, these strategies stand out for their creativity in dealing with the obstacles of forecasting demand.

4.5.3 Limitations and Practical Outcomes

When analyzing the limitations encountered by the authors in the development of their methodologies, as well as their observations regarding practical applications, several similarities among the methods are evident, even across different groups. It is clear that when considering practical application, the robustness of the models is put to the test. The decision by some authors not to implement practical applications, however, does not invalidate the viability of the proposals. Just as practical application alone may not be sufficient to draw concrete conclusions about the efficiency of the method, since the authors often evaluate it in specific scenarios, generalizing the results to other contexts is frequently impractical.

In the diffusion and analogy groups, as well as in the statistical group, there is a noticeable scarcity of applications in real-world scenarios. In diffusion and analogy models, simplicity is a positive aspect, facilitating manipulation. However, recurring challenges include the difficulty of finding suitable analogous products and the limitations in scenarios with high variability. Statistical models, while more complex, require a higher level of technical expertise. The model proposed by Marcek (2007), for instance, utilizes Bayesian probability, which often requires prior knowledge that may not be available, complicating its implementation. Although the other models in the group show promising results, the limited amount of available data has also proven to be a challenge. In addition to requiring the intervention of qualified professionals, statistical models still face limitations in contexts where data are characterized by significant fluctuations.

Hybrid forecasting models outperform statistical and diffusion models due to their ability to combine the strengths of different methods and incorporate new types of data and information. However, certain common issues still persist. Hybrid models that involve

diffusion methods continue to require a database of similar products for implementation. This group emphasises the need of adjustments, parameter calibration, and taking into account external circumstances. Nevertheless, hybrid methods have been tested more in real-world scenarios, although within specific contexts. In contrast, the computational complexity of AI-based approaches poses a significant obstacle. The efficiency of these methods is directly related to processing time and the availability of suitable resources, which might result in higher operational costs. Collection and processing of unstructured data, hyperparameters tuning, and difficulties with generalisation are all regular challenges in the AI group.

Still underexplored, connecting forecasting models with other company systems might improve their reliability and make them more suited to the specific application context. Furthermore, it is important to note that selecting the best forecasting model depends on the application environment, data availability, and resources at hand. Detailed planning can help anticipate and mitigate potential implementation failures of these methods.

4.6 Future Directions

In order to address objective 3 of this research, which aims to analyse the challenges and future opportunities of developing demand forecasts of new products, this section addresses interesting topics to be explored in order to improve current approaches.

4.6.1 Big data

We are entering the big data age, in which massive volumes of data are generated at unprecedented rates and in a variety of formats. Big data's three major characteristics—velocity, variety, and volume—emphasize the need for forecasting models to evolve and adapt in order to deliver more accurate predictions. In the context of new products forecasting, one of the most significant challenges is the limited availability of historical sales data. The earlier decision makers can gain a comprehensive understanding of the market environment in which their products are being introduced, the more strategic advantages they can leverage.

Looking ahead, forecasting models must consider the huge and growing amount of structured and unstructured data available from a wide range of sources. Companies rely extensively on social media networks to share knowledge with consumers about their new products and services, while also enhancing online customer journeys and engagement (DWIVEDI et al., 2021). With a large number of daily users, social media networks have provided marketing a new dimension to evaluate the attitudes and sentiments of real and potential consumers towards their newly launched products (HICHAM; KARIM,

2023). These networks provide real-time data, which enables more dynamic and responsive forecasting. Social media has considerably improved the accuracy of demand forecasting models by providing precise timely information directly from consumers and their social networks (BADULESCU; CAÑAS; CHEIKHROUHOU, 2024).

For instance, the use of web search traffic as a data source was introduced by Lee, Choi e Sohn (2018), but this approach could be further enhanced by incorporating data from social media, videos, images, and other emerging platforms, offering richer insights into consumer behavior and market trends. Badulescu, Cañas e Cheikhrouhou (2024) propose a novel approach that integrates social media information with human judgment to enhance demand forecasting models. Data is collected from social networks, such as Facebook, and a sentiment analysis classifier is employed to identify user comments as positive, negative, or neutral. Subsequently, judgmental adjustments are made by categorizing the information into four impact factors, each reflecting different types of demand fluctuations driven by social media activity. The study emphasizes the relevance of social media data as a valuable resource for demand forecasting, particularly when combined with expert judgment.

Taking advantage of data available beyond traditional sources, including user-generated and real-time data, will be an element to consider into forecasting models. Companies can thus become closer to their customers while also gaining a deeper understanding of market behaviour and trends. It also makes it easier to incorporate ‘word of mouth’ information via social networks, which makes the models increasingly robust and comprehensive. Being able to collect and evaluate a variety of data can be essential to preserving a competitive advantage when launching new products, particularly in complex product markets.

4.6.2 Human-Centric Approach

A human-centric approach to new product demand forecasting has been explored in the literature for some time. Human judgment is essential in uncertain conditions, such as when sales data does not accurately represent real demand (FEILER; TONG; LARRICK, 2012). Recent empirical evidence indicates that demand forecasting models generally assume that sales equal to demand, requiring manual adjustments by forecasters to account for instances when customers were unable to place orders due to stockouts (TONG; FEILER, 2016). These adjustments enable the incorporation of events including promotions, the reflection of pricing changes, or the response to a requirement for ownership. On the other side, these changes can be biased and unnecessary, which harms accuracy (PERERA et al., 2019).

Fildes et al. (2009) conduct a survey to assess the adjustments made to forecasts in four companies, and concluded that some adjustments were trivial and not based on reliable information. They also conclude that positive adjustments were less effective

than negative ones, especially due to the optimism factor of managers. Therefore, a more reliable way of including managers in predictive models, especially based on AI, may be through Explainable AI (XAI). XAI offers a clear understanding of a model's internal processes, including its methods, procedures, and outputs (SARANYA; SUBHASHINI, 2023). In the context of demand forecasting, these explanations are crucial as they help planners identify which model features are the key drivers behind demand estimates. Additionally, XAI plays a vital role in uncovering potential biases within the model and offers valuable insights on how to refine it, ultimately leading to more accurate and reliable forecasts (ROŽANEC; FORTUNA; MLADENIĆ, 2022).

4.6.3 Advancement in the Development of Hybrid Models

Hybrid studies have demonstrated significant potential, not only in the context of demand forecasting, but also in various areas of knowledge. Considering the strengths of different approaches in combination represents an advanced technical improvement. At its essence, an ensemble technique combine results from multiple models, meticulously calibrated before unity. This process maximizes the distinct advantages of individual models while mitigating their limitations. In this way, ensemble methods offer a powerful solution, particularly in scenarios with limited data, by drawing on the combined strengths of several machine learning models (LU; QIU, 2023; IFTIKHAR et al., 2024).

X Li et al. (2024) propose a multi-modal transform-based fusion model for predicting new product sales. The model improves forecasting by extracting visual features, using sequence models for textual and temporal data, applying diffusion modeling for multi-modal interactions, and capturing interconnections between textual, visual, and temporal elements through transform-based architecture. Mejía e Aguilar (2024) introduce a two-phase demand forecasting methodology, where products are first clustered using unsupervised learning based on extracted demand features, followed by evaluating multiple forecasting methods to determine the best-performing models for each cluster. Similarly, Boyang Li et al. (2024) handle complex logistical fluctuations in demand by combining the Multi-scale Time-delay Convolution Model and SARIMA in an ensemble learning technique, with a novel weight assignment strategy to improve forecasting accuracy.

4.7 Conclusion

This study analyzed the performance of quantitative methods in forecasting demand for new products, particularly through the incorporation of artificial intelligence tools. With such a wide variety of studies included, different types of problems were tackled in various ways. Not all the studies reviewed address the issue of insufficient historical sales data, which is understood to be a common problem in forecasting demand for new

products. However, other limitations were presented, such as computational complexities, specialised knowledge, and lack of information on similar products.

Diffusion and analogy-based models have been less explored recently, primarily due to the rapid development of new techniques and tools that demonstrate more precise and suitable performance for the modeling challenges in this area. Statistical and hybrid methods predominantly feature Bayesian approaches, while artificial intelligence methods showcase a wide range of supervised learning techniques, including K-Nearest Neighbors and artificial neural networks. The elucidation of the approaches employed completes the achievement of aim 1.

As for objective 2, comparing the methods is a more relative issue, as it involves several factors, making it difficult to balance different approaches. When analysing evaluation metrics, MAPE was selected because it is the most common among the methods. In this case, hybrid and DL models had the best metrics. Evaluating the models in terms of their robustness and complexity is related to their practical limitations and implications. Complex methods require greater resources, such as qualified personnel and appropriate tools, which may not always be available to every company. In this way, simpler models can be more popular. Given the complexity faced in studies related to short life cycle products, most practical applications are observed in this area, particularly within the fashion industry.

The future of research into forecasting demand for new products is looking promising with the development of AI. Approaches that exploit hybrid modelling to capture different types of data represent a certain advantage. In addition, exploring human participation at the center of forecasts is essential, and the best way to do this in AI approaches is through Explainable AI. Reducing the uncertainty of predictions and using the prior knowledge of managers through a qualitative method increases the reliability of proposals.

The field of demand forecasting for new products is crucial in the planning processes of companies that frequently need to introduce new products to the market. Thus, the rapid evolution of techniques and methodologies aligns with the field's significance, indicating that it will continue to be a highly explored area in the coming years. Finally, as an answer to the research question introduced by this research, it can be concluded that AI tools are effective for forecasting demand for new products, as long as they are used by qualified personnel, with adequate resources and the right information.

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5 Artigo 2: Explainable AI-Based Hybrid Model for New Product Demand Forecasting

Abstract: Forecasting demand for new products remains a persistent challenge due to the absence of historical sales data, which prevents the use of traditional forecasting models. In practice, organisations often turn to managerial judgment and expert intuition to fill this gap; however, such inputs are frequently influenced by optimistic biases and may reduce forecast reliability. To address this issue, this study proposes a forecasting approach that is not only predictive but also inherently interpretable, enabling decision-makers to understand and critically evaluate the drivers behind each estimate. Focusing on the Brazilian electric vehicle market, the proposed hybrid architecture combines multiple AI modelling approaches with SHAP-based explanations, delivering structured forecasts alongside transparent insights into product, market, and socioeconomic influences. The results demonstrate that the model provides stable predictions while offering clear interpretative guidance, supporting managers in making more informed and accountable decisions in data-scarce environments.

Keywords: New Product Demand Forecasting, Electric Vehicles, Explainable Artificial Intelligence, Stacked Ensemble Learning

5.1 Introduction

Demand forecasting constitutes a fundamental component of effective supply chain management and strategic decision-making. It enables organizations to allocate resources efficiently, reduce inventory costs, and respond proactively to market fluctuations. Nevertheless, as product life cycles become increasingly shorter, forecasting the demand for new products has emerged as a critical yet complex task, primarily due to the absence of historical data (VAN STEENBERGEN; MES, 2020). Given the limited availability of both data and suitable analytical tools for predicting demand in such contexts, managers frequently depend on qualitative assessments, expert judgment, surveys, intuition, and heuristic methods to support decision-making (LIN; GOODWIN, 2014; YAMAMURA et al., 2022; SHARMA et al., 2020).

A study conducted by Kahn (2002) over a decade ago revealed that the most common approaches to forecasting the demand for new products include expert judgment, market surveys, and the estimation of average sales based on comparable products. The author also reported that, on average, the forecasting accuracy for new products reached approximately 52% one year after their market introduction. Complementing these findings, empirical analyses of judgmental adjustments in organizational forecasting have

shown that managers’ interventions do not necessarily improve predictive performance. Studies examining real-world forecasting practices across multiple companies reveal that adjustments are often based on weak or unreliable information, tend to follow optimistic biases, and may even be applied in the wrong direction. As a result, many of these corrections fail to add value and can instead degrade forecast accuracy, indicating that judgmental refinements are frequently inconsistent and of limited quality (BROEKE et al., 2019; FILDES et al., 2009).

Nowadays, with the rapid advancement of artificial intelligence research, a new scenario has emerged. AI-based methods have demonstrated remarkable capability to model complex and nonlinear relationships while processing large volumes of both structured and unstructured data, making them particularly suitable for dynamic and uncertain environments. Nair e Huchzermeier (2024) conducted a study aimed at forecasting demand for a German direct-to-consumer brand specializing in premium bicycles. The findings revealed that a machine learning-based forecast relying solely on statistical features reduced the forecasting error by 24%, as measured by the weighted mean absolute percentage error (WMAPE), when compared to purely judgmental predictions. Moreover, an integrated human-machine forecasting approach achieved an additional 14% reduction in error, underscoring that expert judgment remains a critical component in demand forecasting, particularly for rapidly innovating and highly seasonal products.

Building on this evolution in forecasting practices and acknowledging both the limitations of purely judgmental approaches and the potential of data-driven methods, this study examines the challenge of predicting demand for new electric car models in the Brazilian market. We present a hybrid ensemble learning framework that integrates classification and regression tasks, utilizing product specifications, market segmentation data, and regional indicators as input features. A Gradient Boosting Regressor serves as the meta-learner responsible for consolidating the outputs of the base models and generating the final demand estimates. The SHAP values are then employed as an interpretability component of the framework, providing transparent explanations of how each feature influences the predictions and enabling managers to actively engage in analysing and validating the model’s analytical reasoning.

The overarching objective of this research is to evaluate the performance of the proposed forecasting model, particularly regarding the explainability and accuracy of its results, thereby supporting strategic decision-making and offering a reproducible methodological contribution for both academic and industrial applications. The model’s interpretative capacity opens opportunities for a broader and more nuanced understanding of the multiple factors that drive demand, including product attributes, market heterogeneity and socioeconomic conditions of the environment in which the product is introduced. By producing feature-level explanations, the framework facilitates the identification and

contextualisation of drivers that may otherwise remain obscured in purely black-box approaches. To effectively translate these explanatory outputs into actionable insights, the approach relies on a team of professionals with strong analytical skills who can extract, interpret and integrate relevant information into the modelling process, ensuring that the model’s interpretability is converted into robust managerial guidance.

The remainder of this paper is structured as follows. The next section presents the theoretical background related to new product demand forecasting, human judgment and Explainable Artificial Intelligence (XAI). This is followed by the methodological procedures adopted in the study and a detailed description of the proposed model architecture. Subsequently, the empirical results are presented and discussed. The paper ends with the main conclusions and their implications for research and practice.

5.2 Theoretical Background

5.2.1 New product demand forecasting

Forecasting demand for new products differs substantially from forecasting demand for established items. While mature products benefit from accumulated historical data that can be modelled through conventional time-series techniques, new products lack such historical patterns, making it difficult to rely exclusively on traditional quantitative approaches. The absence of sales history, combined with uncertainty regarding consumer adoption, creates a structurally challenging forecasting environment (BAARDMAN et al., 2018; LEE et al., 2014).

According to Kahn (2014), new products may fall into seven categories—cost reduction, product improvement, product line extension, new usage, new (geographical) market, new-to-the-company, and new-to-the-world products. In this study, the focus is placed on product improvement, new usage, new market, and new-to-the-company categories, as these reflect most closely the characteristics of electric vehicles introduced into emerging markets. Despite the inherent uncertainties, Goodwin, Dyussekenewa e Meeran (2013) argue that quantitative methods should remain central in the forecasting process of new products, emphasising that structured analytical approaches continue to play a vital role even in contexts of limited historical information.

To compensate for the lack of demand history, several quantitative approaches have been developed based on the forecasting by analogy principle. These models generate demand forecasts for new products by leveraging data from similar products with established demand patterns (GREEN; ARMSTRONG, 2007). One of the most traditional approaches in this domain is the Bass diffusion model, which captures the early stages of product adoption by modelling consumer behaviour, innovation effects, and word-of-mouth dyna-

mics (LINTON, 2002; YAMAMURA et al., 2022). However, although the Bass model has proven effective for durable goods, it often fails to adequately represent the volatility and short life cycles characteristic (Lin et al., 2023). Furthermore, analogy-based approaches, while practical and widely applied, face a fundamental limitation: the historical demand patterns of analogous products do not necessarily correspond to the future demand of new ones, which may lead to significant forecasting inaccuracies (KAHN, 2014).

In summary, forecasting demand for new products remains a complex task marked by limited historical information, uncertainty in consumer adoption, and the inherent heterogeneity of product categories. Although diffusion and analogy-based models offer valuable starting points, their assumptions and dependence on comparable product histories can restrict their applicability in rapidly evolving markets. These limitations reinforce the need for more flexible and data-driven approaches capable of capturing diverse behavioural, contextual, and market-specific dynamics when historical demand patterns are scarce or unreliable.

5.2.2 Human Judgment

Human judgment has long played a central role in forecasting, particularly in contexts characterized by uncertainty and limited data. The term judgmental forecasting has been used in the literature to encompass a broad set of practices, ranging from forecasts generated purely through expert judgment to judgmental adjustments of statistical forecasts and hybrid approaches that combine quantitative outputs with human input (PERERA et al., 2019). Evidence from industry surveys indicates that the adjustment of statistical forecasts through managerial judgment is widespread and commonly adopted in practice, reflecting both the limitations of purely quantitative models and the perceived value of contextual knowledge held by decision-makers (LIN; GOODWIN, 2014).

To structure these practices, Sanders e Ritzman (2004) proposed four methodological categories for integrating judgment with quantitative forecasting: judgmental adjustment of a statistical forecast; statistical correction of a judgmental forecast; explicit combination of quantitative and judgmental forecasts—often through a weighted average; and the use of judgment as an input to model development. These categories highlight the multiple ways through which human expertise can inform, complement, or modify algorithmic predictions.

Despite its prevalence, researchers have emphasized that judgmental adjustments should be applied selectively. Wibowo (2023) recommends that such interventions be made only when forecasters possess specific contextual information unavailable to statistical models or when quantitative methods become less reasonable due to heightened uncertainty. Similarly, the findings of Alvarado-Valencia et al. (2017) suggest that adjustments should occur exclusively when analysts demonstrate substantial expertise and when confidence

in statistical forecasts is relatively low. Together, these studies underscore the need to calibrate the influence of human judgment rather than applying adjustments routinely or intuitively.

More recently, empirical evidence has shown that integrating human expertise with machine learning (ML) can yield superior forecasting performance. Nair e Huchzermeier (2024) demonstrate this by comparing the out-of-sample accuracy of (i) judgmental forecasts, (ii) ML-only forecasts, and (iii) an integrated human–machine approach. Their results indicate that the integrated method achieves the highest accuracy—33% WMAPE on the evaluated dataset—highlighting the additive value of expert insight when combined systematically with quantitative models, particularly in forecasting innovative seasonal products.

This body of evidence raises an important question: how can the role of human judgment in forecasting be optimized through a more analytical and data-oriented approach? The present study addresses this issue by exploring the use of Explainable Artificial Intelligence (XAI) techniques to clarify and interpret model behavior, thereby providing forecasters with transparent insights that enhance human–machine collaboration in new product demand forecasting.

5.2.3 Explainable Artificial Intelligence

The “black-box” problem in artificial intelligence refers to the difficulty of understanding the internal reasoning of complex models and the lack of transparency regarding how specific decisions are reached. In this context, the principle of explainability is closely tied to interpretability, as methods are considered explainable when their internal operations can be meaningfully understood by human users. Although “explainable” has become the dominant term in the XAI literature, the notion of interpretability remains equally relevant when addressing the comprehensibility of model behavior (ALI et al., 2023). Accordingly, XAI research seeks to enhance the transparency of AI systems without compromising predictive performance, enabling users to trace decision paths, detect potential distortions or biases in the training data, and ensure that models operate as intended (ADADI; BERRADA, 2018; AMIRI et al., 2021).

Explainability can be pursued at both the global and local levels. Global explanations provide insights into the overarching logic and behavior of a forecasting model, whereas local explanations elucidate the specific factors influencing individual predictions. In demand forecasting, such human-understandable explanations are particularly valuable, as they allow planners to identify the most influential predictors, detect systematic biases, and recognize opportunities to improve model performance (ROŽANEC; FORTUNA; MLADENIĆ, 2022). To address these needs, Rožanec, Fortuna e Mladenović (2022) proposed an XAI architecture that integrates semantic technologies with AI-based forecasting

models and demonstrated its effectiveness in real-world applications. A key component of their approach is the use of a knowledge graph, which supports higher-level, concept-driven explanations that go beyond traditional feature-based interpretations and offer decision-makers a more holistic understanding of how demand estimates are produced.

As organizations increasingly rely on complex predictive systems, XAI has become essential for ensuring responsible and trustworthy deployment. Its contributions are often articulated through four complementary objectives. First, explain to justify provides users with the rationale behind a prediction, a crucial requirement in settings governed by regulations such as the GDPR and its “Right to Explanation.” Second, explain to control enables practitioners to identify inconsistencies, vulnerabilities, or flawed reasoning, preventing erroneous outputs from influencing operational decisions. Third, explain to improve supports continuous refinement by revealing weaknesses or limitations within the model, thereby facilitating the development of more accurate and robust forecasting systems. Finally, explain to discover helps uncover previously unknown patterns or domain knowledge, generating new insights that enrich understanding of the forecasting problem (SARANYA; SUBHASHINI, 2023).

In this context, incorporating XAI into demand forecasting becomes particularly relevant for new products, where uncertainty is high and transparent reasoning is essential for decision-making. In this study, explainability is achieved through SHAP values, which provide consistent local and global insights into how each feature contributes to the predicted demand. By integrating SHAP into the proposed hybrid architecture—composed of a classifier, a regressor, and a stacking-based meta-model—we demonstrate that high predictive performance can be combined with interpretability. This integration not only supports more informed and accountable decision-making but also enhances the transparency of the model’s internal logic, creating a foundation for practical adoption in managerial settings.

5.3 Methodology

5.3.1 Data Description

The dataset employed in this study was constructed by merging three distinct sources: (i) monthly sales records by geographic region (**Sales**), (ii) technical and market-related characteristics of the vehicles (**Features**), and (iii) contextual regional indicators (**Region**). The purpose of this integration was to build a unified and comprehensive database that incorporates both product-specific and environmental information relevant to the commercial performance of electric vehicles.

The final structure includes the 25 electric vehicle models with the highest mar-

ket share in Brazil during the period from 2023 to 2024, comprising monthly records disaggregated by region.

The main variables included are as follows:

- **Sales:** *model, region, year, month, sales;*
- **Features:** *model group, model, brand, price (Oct/24), price (Jun/25), price variation, drivetrain type, bodystyle, market segment, autonomy, energy consumption, embedded technology, warranty, average maintenance cost, ground clearance, trunk capacity, number of airbags;*
- **Region:** *region, total orders, regional GDP, charging points, fiscal incentives, urbanization rate.*

The merging process was conducted through relational joins using two primary keys: *model* and *region*. The **Features** table contains one unique entry per vehicle model and was joined to the **Sales** table using the *model* column. Likewise, the **Region** table, with one row per region, was merged into the **Sales** table using the *region* key.

Before merging, preprocessing steps included standardizing string values (e.g., accents, case sensitivity), ensuring data type consistency, and handling missing values using imputation or exclusion based on data quality thresholds. The final integrated dataset has a star schema-like structure, where **Sales** acts as the fact table and the other two as dimension tables.

Figure 19 presents the entity-relationship (ER) diagram that summarizes the structure and relationships among the datasets.

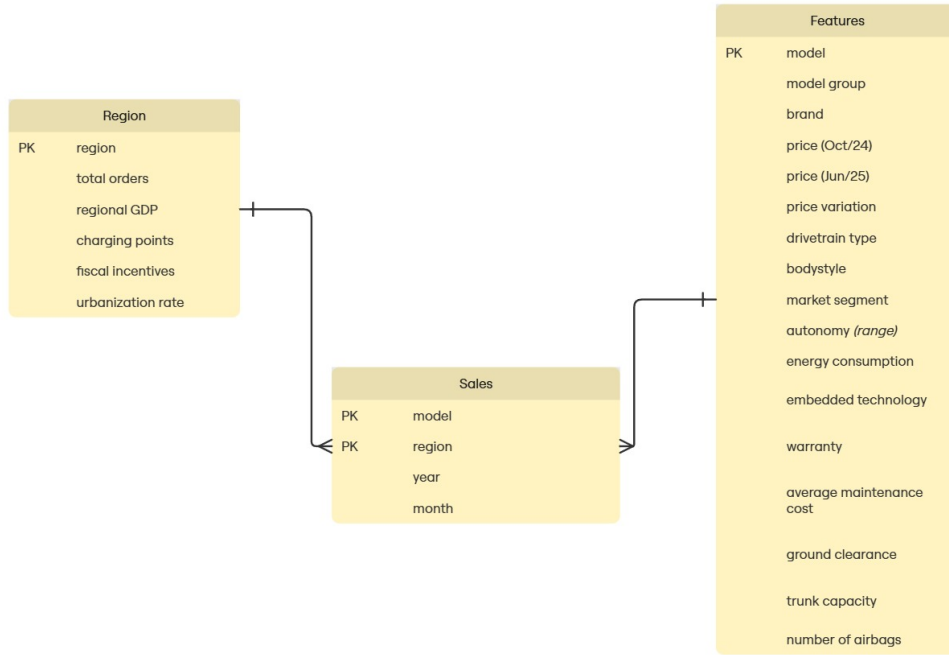


Figura 19 – Entity-Relationship (ER) diagram representing the relational structure of the integrated database.

5.3.2 Forecasting Model: Ensemble Learning with Stacking

To address the challenge of forecasting demand for new products—a scenario marked by limited historical data and high uncertainty—this study adopts an ensemble learning approach based on the stacking technique. The objective is to combine predictions generated by distinct base models (base learners), each handling a complementary task, and consolidate them using a meta-model (meta learner) that produces the final demand estimate.

The overall architecture involves three main stages:

1. Base learners:

- A *classification model* (XGBoost Classifier), trained using product characteristics to estimate the expected demand profile (e.g., low, medium, high);
- A *regression model* (XGBoost Regressor), trained using the time series of historical sales to generate continuous demand predictions.

2. Generation of intermediate predictions:

- Each base model outputs an independent prediction, comprising a demand class and a numerical estimate.

3. Meta learner (stacking model):

- A regression model (Gradient Boosting Regressor) receives as input the outputs from the base learners, along with auxiliary features, to generate the final demand forecast;
- This meta-model was chosen for its ability to capture nonlinearities and interactions between the outputs of the previous models.

This hierarchical strategy allows the limitations of individual models to be mitigated by leveraging their complementary strengths. Furthermore, the architecture is fully compatible with Explainable Artificial Intelligence (XAI) techniques—such as SHAP—enabling the interpretation of feature contributions throughout the entire predictive pipeline.

The use of stacking ensembles for structured data has demonstrated strong performance in demand forecasting and related tasks (**seyam2025stacking**). Recent studies emphasize that stacking enables better generalization by reducing bias and variance through the layered architecture (**chien2023ensemble**).

5.3.3 Proposed Forecasting Architecture

Figure 20 presents the conceptual framework of the proposed forecasting model. The architecture is based on a hybrid ensemble learning strategy that integrates multiple predictive layers with explainability resources to estimate demand for new products, particularly in contexts where historical sales data is limited or unavailable.

The model is structured in two main phases: training and deployment. During training, the available data is processed and used to develop two parallel learning components. The first is a classification model that learns to assign demand levels—such as low, medium, or high—based on vehicle specifications and contextual information. The second is a regression model trained to estimate the continuous sales volume for each vehicle-region-month combination. Both models operate independently but are trained on the same aligned dataset.

The outputs of these two models—namely the predicted demand class and the numerical forecast—are concatenated and used as input for a meta-model. This final layer is implemented using a Gradient Boosting Regressor, which captures nonlinear interactions between the base predictions and refines the final demand estimation.

Once trained, the complete model pipeline can be applied to unseen products using only their descriptive attributes and contextual features. Throughout the architecture, explainable artificial intelligence (XAI) techniques, particularly SHAP values, are incorporated to assess the relative importance of each feature and provide transparency in the forecasting process. This structure allows for interpretable, data-driven decision-making, supporting organizations in planning and launching new products more effectively.

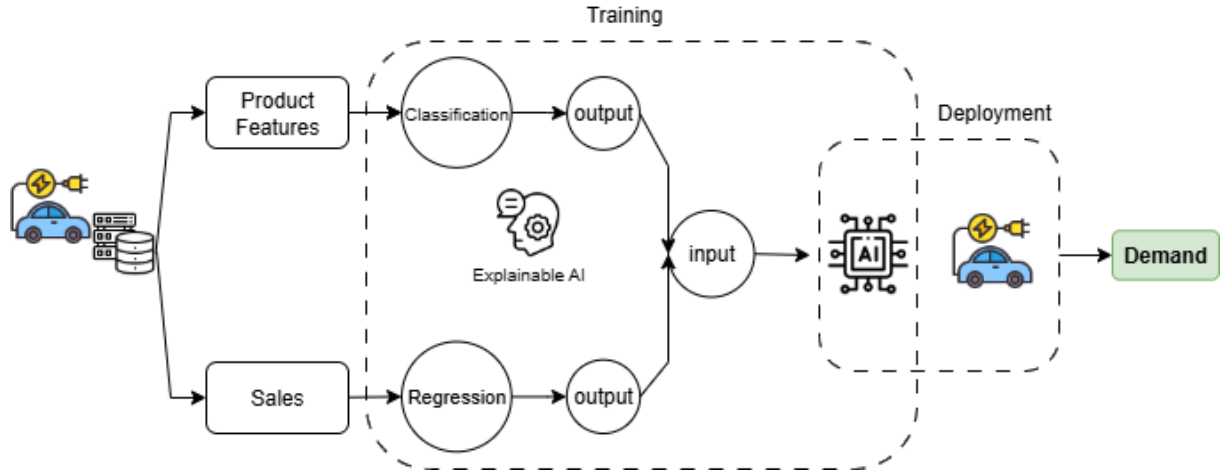


Figura 20 – Conceptual framework of the proposed hybrid forecasting model with explainable AI.

5.3.4 Experimental Design

This section presents the experimental procedures used to evaluate the performance and interpretability of the proposed hybrid forecasting model. The process encompassed data preprocessing, model training, validation, residual analysis, and explainability assessment, with all steps designed to simulate real-world conditions of demand forecasting for new product launches in the electric vehicle market.

Prior to model training, a comprehensive feature engineering process was implemented to ensure data quality and maximize predictive performance. Numerical features were standardized or normalized where appropriate, while categorical variables were encoded using label encoding techniques. Missing values were addressed through imputation based on median values, or excluded entirely when the degree of incompleteness was significant. These preprocessing steps ensured a consistent and reliable input space for both the classification and regression components of the hybrid model.

The dataset was divided into three subsets: training (70%), validation (15%), and testing (15%), following a stratified splitting strategy to maintain representative distributions of vehicle models and sales volumes. To replicate the realistic scenario of forecasting demand for new products without historical sales data, vehicle models appearing in the test set were excluded from both the training and validation sets. The validation set was used exclusively for hyperparameter tuning and early stopping, thereby preventing information leakage and overfitting. In the classification stage, demand levels were constructed by discretizing the target variable (monthly sales) into three classes: low, medium, and high. Thresholds were empirically defined using sales distribution quantiles to achieve balanced class representation. This qualitative demand profiling allowed the

classification model to provide a market positioning perspective, which was later integrated with the regression output in the ensemble learning framework.

Model performance was evaluated through multiple regression metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2). Additionally, residual analysis was performed to detect potential systematic prediction errors and to examine residual distributions across product categories and regions. These analyses provided further insights into the robustness and generalization capabilities of the proposed model, as well as identifying possible biases related to specific segments or market conditions.

To ensure the interpretability of the proposed forecasting approach, SHAP (SHapley Additive exPlanations) was incorporated as a model-agnostic explainability technique. The method was applied to each base learner — the classification and regression models — during the training stage of the proposed pipeline. This allowed the computation of both global and local feature attributions, capturing the marginal contribution of each input variable to the predicted output while preserving the internal logic of the underlying algorithms. The adoption of SHAP at this stage was designed to provide a systematic and consistent evaluation of feature influence across different learning tasks, ensuring that the interpretability assessment was embedded within the model development process.

All experiments were conducted using Python 3.11, employing the `xgboost`, `scikit-learn`, and `shap` libraries.

5.4 Results and Discussion

5.4.1 Predictive Performance of the Models

The performance of the predictive models was evaluated using common regression metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), as well as the coefficient of determination (R^2). Table 9 presents the results for each base learner and the meta-learner.

Tabela 9 – Evaluation Results of the Forecasting Models

Model	Set	MAE	RMSE	R^2	Accuracy
XGBoost Classifier	Validation	-	-	-	0.8555
XGBoost Classifier	Test	-	-	-	0.8689
XGBoost Regressor	Validation	16.65	42.86	0.8530	-
XGBoost Regressor	Test	26.77	103.98	0.4493	-
Meta-Model	Validation	0.421	0.561	0.895	-
Meta-Model	Test	0.620	0.856	0.778	-

The evaluation results reveal distinct behaviors between the base models and the stacked architecture. The classification stage maintained stable accuracy across validation and test sets, indicating robustness in assigning demand profiles to unseen products. In contrast, the regression stage exhibited signs of overfitting, as evidenced by the substantial drop in R^2 and the sharp increase in RMSE from validation to test data. This suggests that, although the base regressor captured patterns well during validation, its generalization capacity to new instances was limited.

The meta-model mitigated these limitations by integrating the outputs from both the classifier and regressor. Its lower error rates and higher R^2 on the test set demonstrate improved predictive stability and reduced overfitting. These gains underscore the value of the stacking approach in leveraging complementary information from different models, enhancing the overall accuracy and robustness of demand forecasts, particularly in the context of new product launches where historical data is scarce.

5.4.2 Residual Analysis

To evaluate the consistency and adequacy of the forecasting model, residual analyses were performed. The two main visualizations used are the Residuals vs. Predicted plot and the QQ Plot of Residuals.

Residual analysis is a crucial step in verifying the assumptions underlying a regression model and ensuring the reliability of its predictions. Figure 21 displays the residuals plotted against the predicted values. Ideally, this plot should reveal a random scattering of points centered around the zero line, without any clear patterns. Such a distribution indicates that the model successfully captured the underlying structure of the data and that the residuals behave as random noise. In this case, the residuals appear to be relatively symmetrically distributed, with no severe clustering or curvature, although a slight increase in dispersion is noticeable as predicted values increase — a mild indication of heteroscedasticity. Nonetheless, the absence of systematic patterns suggests that the model is not misspecified and that the majority of relevant features were considered during training.

The **QQ Plot of Residuals** shown in Figure 22 serves to assess the normality assumption of the residuals, which is important for the validity of statistical inference. In a well-behaved model, residuals should follow a normal distribution, and the points in the QQ plot should closely follow the 45-degree reference line. In the present case, the central portion of the residuals aligns reasonably well with the theoretical quantiles, while mild deviations are observed at the tails. These deviations suggest the presence of moderate skewness or potential outliers, but not to an extent that would invalidate the general predictive behavior of the model.

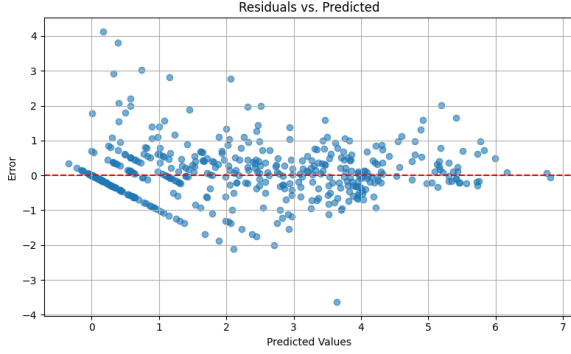


Figura 21 – Residuals vs. Predicted

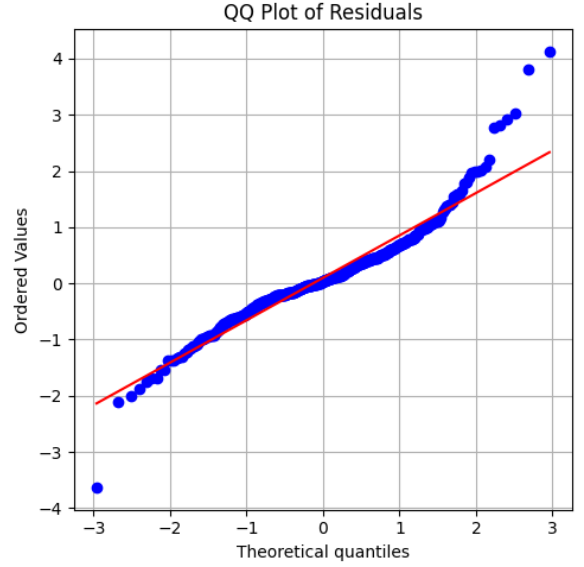


Figura 22 – QQ Plot of Residuals

Figura 23 – Analysis of Model Residuals

Taken together, these diagnostic plots provide strong evidence that the residuals of the meta-model are largely well-behaved. The relatively random dispersion of points in the residual plot and the close adherence to normality in the QQ plot suggest that the assumptions of homoscedasticity and residual normality are mostly satisfied. These findings reinforce the robustness of the model and increase confidence in its forecasting ability for new product demand.

5.4.3 Explainability and Feature Importance

To enhance the interpretability of the proposed models, SHAP (SHapley Additive exPlanations) values were computed. This allowed both a global and local understanding of how each feature contributes to the predictions, providing transparency in the decision-making process.

Figure 24 shows the global feature importance for the classification model across the three demand profiles defined in this study: low demand (class 0), medium demand (class 1), and high demand (class 2). *Warranty* emerges as the most influential variable, with a particularly strong impact on the low-demand profile. This suggests that, for products with lower sales potential, extended warranty coverage can act as a compensatory factor, increasing their perceived value and raising the probability of migrating towards higher demand profiles.

Recharge is the second most relevant feature, with slightly higher influence on low- and medium-demand profiles, indicating that charging convenience is particularly

decisive for products with less market consolidation. *Price_variation* shows a balanced but significant effect across all profiles, indicating that price instability consistently reduces the probability of belonging to higher demand segments. Conversely, *Price_(06/25)*, representing the current price level, has greater influence on medium and high demand profiles, suggesting that absolute price positioning becomes more critical as market potential increases.

Physical attributes such as *Ground_clearance* and *Consumption* have moderate importance, contributing mainly to distinctions between low and medium demand. In contrast, variables such as *Type*, *Category*, and *Region_S* have limited discriminatory power in this dataset. Macroeconomic variables, including *GDP* and *Incentive*, although less impactful globally, tend to play a slightly more prominent role in medium and high demand profiles, indicating that favorable economic contexts and government incentives strengthen already well-positioned products.

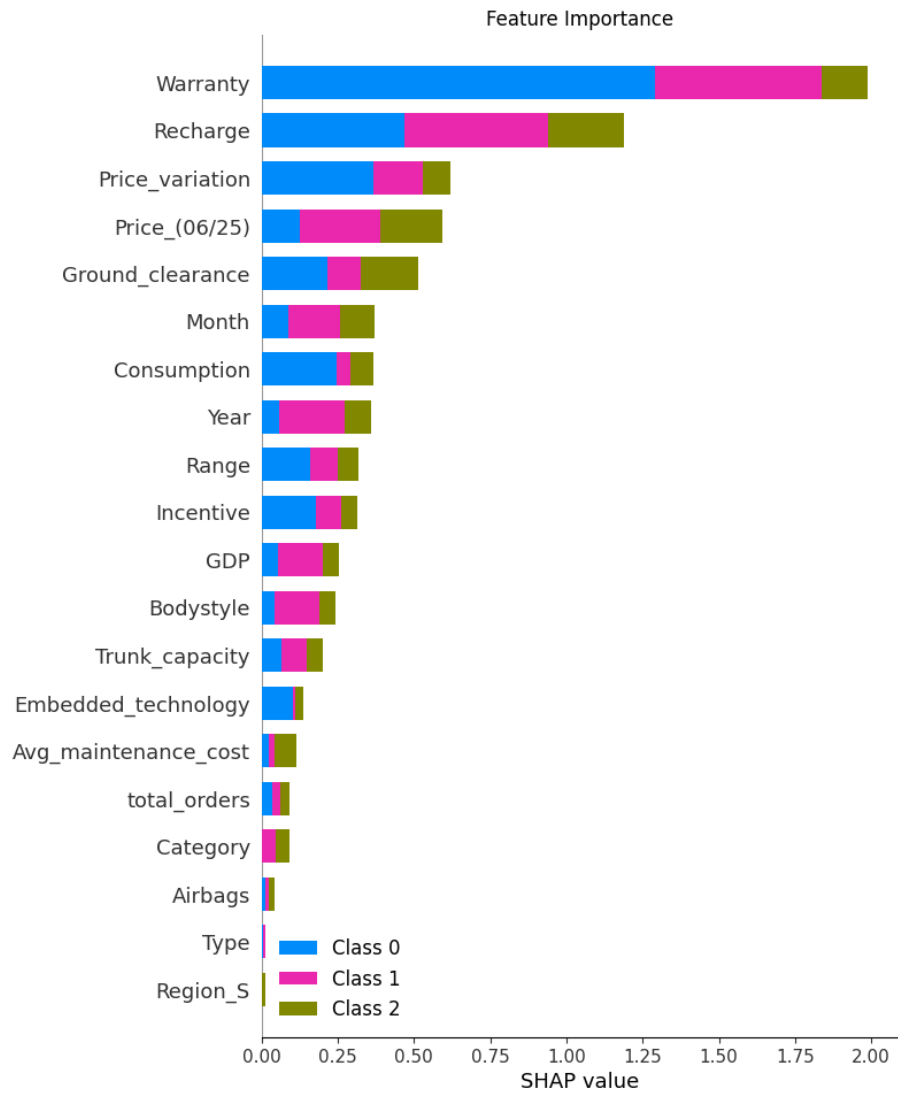


Figura 24 – SHAP feature importance for the classification model.

Figure 25 presents the SHAP summary plot for the regression model, which predicts expected sales volume. The variables are ordered according to their mean absolute SHAP value, indicating their overall importance. Each point represents an observation from the dataset, where the horizontal position shows whether the feature value increases (right) or decreases (left) the predicted sales, and the color represents whether the feature value is high (pink) or low (blue).

Among the leading variables, *Warranty* again stands out: higher warranty values tend to increase predicted sales, while shorter warranty periods reduce them. *Recharge* follows a similar pattern, with greater availability and convenience of charging infrastructure positively influencing sales forecasts. Conversely, high *Price_variation* values are concentrated on the left side of the plot, indicating a negative effect on demand, while stable prices contribute positively.

A particularly relevant technical characteristic is *Range* (driving autonomy). The analysis reveals that lower values of autonomy (blue) are predominantly associated with negative SHAP values, meaning they reduce the model's predicted sales. This finding aligns with consumer behavior in the electric vehicle market, where limited range is perceived as a functional constraint, lowering product attractiveness and market potential. In contrast, higher range values (pink) shift predictions upward, reinforcing their importance as a competitive differentiator.

Other factors, such as *Year*, *Incentive*, and *GDP*, also contribute positively under favorable conditions, reflecting temporal effects, governmental support, and macroeconomic contexts that can amplify demand. The combined interpretation of the classification and regression SHAP results enables a deeper understanding of both the drivers and the magnitude of demand, supporting more informed strategic decisions.

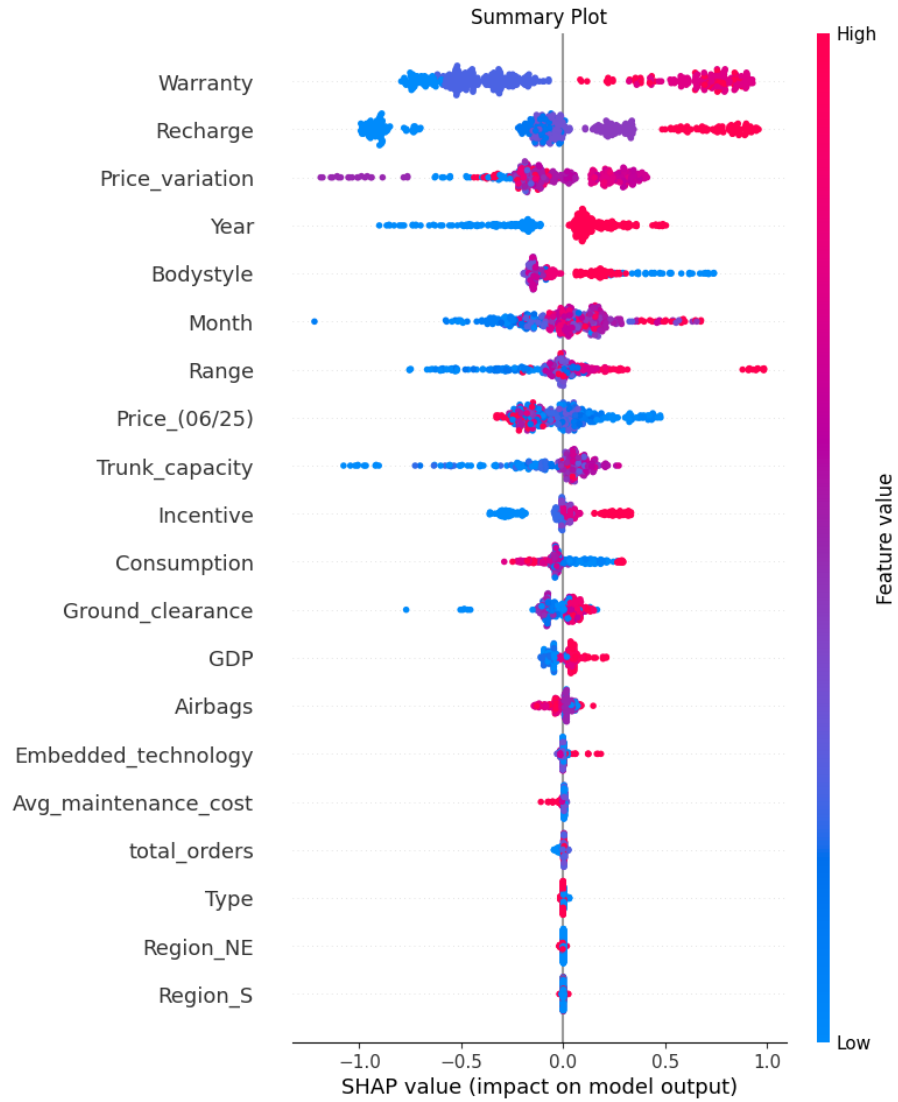


Figura 25 – SHAP summary plot for the regression model.

5.5 Conclusion

This study proposed a hybrid forecasting architecture capable of generating reliable demand estimates for new products, even in the absence of historical sales data. The approach proved particularly relevant for industries with short product life cycles and frequent launches, such as the electric vehicle sector. By combining classification and regression within an explainable artificial intelligence framework, the model delivers both quantitative predictions and qualitative demand profiling, thereby enabling more informed strategic decisions.

The integration of SHAP-based explainability enhanced the transparency of the forecasting process, revealing which product and market attributes most strongly influence demand. High vehicle autonomy and favorable fiscal incentives emerged as consistent

positive drivers, while price instability was shown to negatively affect forecasts. These insights provide actionable guidance for marketing, pricing, and product development strategies, allowing managers to prioritize attributes that significantly contribute to sales performance.

From a managerial standpoint, the capacity to merge predictive outputs with interpretable explanations offers a competitive advantage in early product planning. The transparent pipeline developed in this research facilitates robust scenario analysis, risk assessment, and resource allocation by linking product features, regional conditions, and predicted market responses. This alignment between analytical modeling and business objectives strengthens decision-making processes and supports proactive market positioning.

Future research could explore the extension of this framework to multi-market or cross-country contexts, evaluating the stability of feature importance across different cultural and economic environments. Additionally, incorporating dynamic pricing simulations, real-time data integration, or reinforcement learning strategies could further enhance forecast adaptability. These directions would expand the applicability of the proposed model and provide deeper insights into the evolving dynamics of demand for emerging technologies.

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6 Síntese dos Resultados

A presente dissertação é estruturada em duas etapas complementares, elaboradas no formato de compêndio de artigos, cujos resultados estão interligados. No primeiro artigo, foi desenvolvido uma revisão sistemática da literatura para delinear o panorama da previsão de demanda de produtos novos, classificando as abordagens observadas na literatura em quatro grandes grupos: modelos baseado em difusão e analogia, modelos estatísticos, modelos híbridos e modelos baseados em inteligência artificial. Essa etapa serviu não apenas para mapear os algoritmos mais utilizados e as métricas de avaliação de desempenho, mas também possibilitou uma análise crítica das limitações que frequentemente se repetem na área, como a dificuldade em lidar com a falta de histórico de vendas, a baixa interpretabilidade de modelos complexos e a escassez de estudos voltados para aplicações práticas.

Ao final do primeiro artigo do compêndio, destaca-se duas direções promissoras para o progresso da área: a busca por soluções híbridas que integrem diversos paradigmas, visando aprimorar o desempenho preditivo; e a adoção de uma visão *human-centric*, onde se busca a inclusão dos fatores humanos em posições estratégicas da etapa de previsão de demanda. Portanto, foi definido que técnicas de explicabilidade (SHAP) contribuiriam para a abordagem *human-centric* quando utilizamos uma abordagem de Inteligência Artificial. Essas orientações conceituais foram a base para a elaboração do segundo artigo.

O segundo artigo da dissertação, concretizou essas perspectivas futuras, definidas no primeiro artigo, ao sugerir e testar um modelo híbrido baseado em *ensemble learning*, que combina dois modelos base — um classificador e um regressor, ambos do tipo XGBoost — em um meta-modelo Gradient Boosting Regressor. Esta configuração foi criada para tirar proveito das forças complementares de cada método: a classificação fornece um enquadramento qualitativo ao antecipar o perfil de demanda (baixa, média ou alta); por sua vez, a regressão adiciona granularidade numérica ao estimar quantitativamente as vendas. A junção no meta-modelo possibilitou unir as previsões, o que resultou em maior acurácia e generalização em relação aos modelos que foram utilizados de forma isolada. Além disso, a utilização de um meta-modelo através desta estrutura corrigiu problemas de *overfitting* das previsões base, o que evidencia a robustez do método proposto.

A abordagem *human-centric* foi implementada com a ajuda de métodos de XAI, mais especificamente com os valores SHAP, que foram aplicados aos modelos base durante o treinamento. Isso possibilitou uma identificação clara e transparente dos principais fatores que influenciam a previsão, fornecendo aos tomadores de decisão não apenas o resultado em si, mas também o raciocínio por trás das estimativas. Essa integração assegura que

o modelo sirva como um suporte para a tomada de decisões, e não como um substituto, seguindo a diretriz de manter o ser humano como o protagonista no processo decisório.

Em conjunto, o percurso da pesquisa progride da *síntese crítica à prova empírica*: a revisão sistemática delinea o campo e explicita lacunas; seus requisitos (métricas, critérios de interpretabilidade e integração de variáveis técnicas e contextuais) orientam a modelagem, que é implementada e testada em cenário real. As evidências geradas alimentam o referencial teórico e convergem para um método que é replicável, transparente e voltado para a tomada de decisão, capaz de integrar desempenho preditivo e explicabilidade, possuindo potencial de aplicação em outros campos. A Tabela 10 evidencia essa coerência ao correlacionar, para cada componente, objetivos, resultados e contribuições. Percebe-se uma sequência progressiva em que a fundamentação teórica possibilita a modelagem, enquanto a avaliação válida, por meio de métricas e explicações, os objetivos estabelecidos, interligando teoria e prática com produtos científicos que são complementares e rastreáveis.

Tabela 10 – Síntese dos objetivos, resultados e contribuições

Componente	Objetivos	Resultados	Contribuições
Artigo 1	Mapear, consistentemente, as abordagens utilizadas para previsão de demanda de novos produtos, através de uma revisão sistemática da literatura.	(01) Panorama do tema e evolução recente; (02) Taxonomia em quatro grupos (difusão/analogia, estatísticos, IA e híbridos); (03) Lacunas; (04) Direções futuras: integração híbrida e uso de XAI em abordagem <i>human-centric</i> .	Definição de requisitos de projeto (métricas, critérios de interpretabilidade e variáveis contextuais) que orientam a etapa de modelagem.
Artigo 2	Propor e avaliar um modelo híbrido explicável: classificador + regressor integrados por <i>stacking</i> com meta-modelo Gradient Boosting, aplicando-o à previsão de demanda de veículos elétricos no Brasil.	(01) Desempenho superior ao de modelos base isolados; (02) Maior robustez e generalização; (03) Explicações coerentes via valores SHAP, com identificação de preditores relevantes; (04) Evidências aplicáveis a decisões de lançamento, precificação e posicionamento.	Contribuição metodológica ao demonstrar combinação de desempenho e transparência em cenário real; entrega de um pipeline reproduzível e orientado à decisão; aproximação entre teoria (síntese do Artigo 1) e prática (validação empírica).

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