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CONTACTS
Email: *technoeconomics @spbstu.ru*
Web: *https://technoeconomics.spbstu.ru/en*

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THE MODERATING ROLE OF INTERNET ACCESSIBILITY ON CONSUMER ONLINE SHOPPING INTENTION IN INDONESIA

Wiryanta Muljono[1] ✉, Sri Setiyawati[2], Padmanabha Adyaksa Setyanto[3]

[1] Ministry of Communication and Information Technology, Jakarta, Indonesia;
[2] Moestopo University, Jakarta, Indonesia;
[3] Bandung Institute of Technology, Bandung, Indonesia

✉ wiryantamuljono@gmail.com

Abstract. The rapid advancement of digital technology has significantly shifted consumer behavior, leading to massive growth in Indonesia's e-commerce landscape. This study aims to develop and test a model that explains the formation of consumer Attitude and Online Shopping Intention by examining the influence of key antecedents: Convenience and Startup Credibility, while integrating the unique role of Internet Accessibility. The research is crucial in the context of developing nations like Indonesia, where varying internet infrastructure necessitates a deeper understanding of its impact. Using quantitative research methods, the data collected from internet users in major Indonesian economic regions (Jabodetabek, Joglosemar, and Gerbang Kertosusila) was analyzed using Partial Least Square (PLS). The findings confirmed that Convenience and Startup Credibility have a positive and significant influence on both Attitude and Online Shopping Intention. Furthermore, a positive Attitude is a significant predictor of Online Shopping Intention. Critically, the study found that Internet Accessibility acts as a significant moderator, strengthening the relationship between Convenience and Online Shopping Intention, Startup Credibility and Attitude, and Attitude and Online Shopping Intention. However, the moderating effect was not supported for the Convenience → Attitude and Credibility → Intention paths, suggesting that in certain high-penetration urban areas, accessibility may function more as a direct antecedent or is already perceived as adequate. This research provides a modified model, highlighting the critical importance of internet infrastructure (accessibility) as an uncontrollable but essential variable that fundamentally determines the success of e-commerce adoption in Indonesia.

Keywords: online shopping, intention, convenience, startup credibility, attitude, internet accessibility, ecommerce

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ПОСРЕДНИЧЕСКАЯ РОЛЬ ДОСТУПНОСТИ ИНТЕРНЕТА В ФОРМИРОВАНИИ НАМЕРЕНИЙ ПОТРЕБИТЕЛЕЙ СОВЕРШАТЬ ОНЛАЙН-ПОКУПКИ В ИНДОНЕЗИИ

Вирьянта Мулджоно[1] ✉, Шри Сетиявати[2],
Падманабха Адьякса Сетьянто[3]

[1] Министерство связи и информационных технологий, Джакарта, Индонезия;
[2] Университет Моэстопо, Джакарта, Индонезия;
[3] Бандунгский технологический институт, Бандунг, Индонезия

✉ wiryantamuljono@gmail.com

Аннотация. Быстрое развитие цифровых технологий значительно изменило поведение потребителей, что привело к масштабному росту электронной коммерции в Индонезии. Цель данного исследования — разработать и протестировать модель, объясняющую формирование отношения потребителей к интернету и намерения совершать онлайн-покупки, изучив влияние ключевых факторов: удобства и доверия к стартапу, а также интегрировав уникальную роль доступности интернета. Исследование имеет решающее значение в контексте развивающихся стран, таких как Индонезия, где различная интернет-инфраструктура требует более глубокого понимания ее влияния. С помощью количественных методов исследования были проанализированы данные, собранные у интернет-пользователей в основных экономических регионах Индонезии (Джабодетабек, Джоглосемар и Гербанг Кертосусила), с использованием метода частичных наименьших квадратов (PLS). Результаты подтвердили, что удобство и доверие к стартапу оказывают положительное и значимое влияние как на отношение к интернету, так и на намерение совершать онлайн-покупки. Кроме того, положительное отношение является значимым предиктором намерения совершать онлайн-покупки. Важно отметить, что исследование показало, что доступность интернета выступает в качестве значимого посредника, усиливая взаимосвязь между удобством и намерением совершать онлайн-покупки, репутацией стартапа и его отношением, а также отношением и намерением совершать онлайн-покупки. Однако посреднический эффект не подтвердился для путей «Удобство → Отношение» и «Репутация → Намерение», что предполагает, что в некоторых городских районах с высокой степенью проникновения интернета доступность может выступать скорее в качестве прямого предшественника или уже восприниматься как достаточная. Данное исследование предлагает модифицированную модель, подчеркивающую критическую важность интернет-инфраструктуры (доступности) как неконтролируемой, но важной переменной, которая коренным образом определяет успех внедрения электронной коммерции в Индонезии.

Ключевые слова: онлайн-шопинг, намерение, удобство, авторитет стартапа, отношение, доступность интернета, электронная коммерция

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Introduction

Background and Research Phenomenon

The rapid advancement of Information Technology (IT) has catalyzed a profound digital transformation across global civilization, fundamentally altering consumer behavior and spurring the growth of online shopping (eCommerce). In Indonesia, this phenomenon is particularly pronounced, supported by high rates of internet and smartphone penetration (APJII, 2019; Kemp, 2019). Online shopping is defined as the transaction process between two parties involving the exchange of goods or information, mediated primarily by the internet (Indrajit, 2001; Lee, 2001).

This rapid growth, often driven by disruptive innovation, creates vast opportunities for Micro, Small, and Medium Enterprises (MSMEs), which constitute 99% of businesses in Indonesia and are major contributors to the digital economy (Singapore Post, 2014; As'ad & Ahmad, 2012). Conversely, this digital shift presents a significant challenge to traditional retail, forcing conventional stores to re-evaluate or close (Detik Finance, 2017). Theoretical literature consistently identifies several core psychological and platform-based antecedents that shape consumer purchasing decisions and drive Online Shopping Intention (OSI). These core determinants include: Convenience: Defined as flexibility, ease of product selection, and transaction security (Meuter et al., 2000; Berry et al., 2002). Startup Credibility: The consumer's trust in the e-commerce website, which is vital for reducing concerns such as the misuse of personal data (Turban, 2001; Koufaris & Hampton-Sosa, 2004). These factors underpin the formation of a positive Attitude toward online shopping, which ultimately precedes the consumer's intention to purchase (Yang et al., 2007).

Problem Statement and Theoretical Gap

Despite the robust growth of eCommerce and the established reliance on these core determinants (Convenience, Credibility, and Attitude), the success of online retail in developing, archipelagic economies like Indonesia remains fundamentally subject to significant infrastructural constraints. While studies in developed nations often treat robust internet Accessibility as a non-issue (Evers, 2002; Jongen, 2017), research confirms that emerging markets face formidable challenges due to unreliable internet connections, poor availability, and low network penetration rates (Molla & Licker, 2005).

This dependency suggests that the perceived efficiency benefits of Convenience and the assurance provided by Credibility are fundamentally contingent upon the underlying network quality. The relationship between these psychological and platform-based factors and consumer intention is therefore unlikely to be uniform across all markets.

The critical theoretical gap lies in the failure of existing behavioral models to explicitly conceptualize and test the role of Internet Accessibility as a moderating mechanism within the process of attitude and intention formation. This omission constitutes an empirical void, particularly in regions where accessibility is an uncontrollable, determining factor for the consumer experience.

Research Objectives and Novelty

This study addresses the theoretical and empirical void by developing and testing a comprehensive model focused on the Indonesian market. The primary objective is to investigate the direct influence of Convenience and Startup Credibility on Attitude and Online Shopping Intention, and, critically, to examine how Internet Accessibility moderates all links between these antecedents and the formation process of both attitude and intention.

The study seeks to answer the following core research questions:

1. Does Convenience influence Attitude and Online Shopping Intention?
2. Does Startup Credibility influence Attitude and Online Shopping Intention?
3. Does Attitude influence Online Shopping Intention?
4. How does Internet Accessibility moderate the influence of Convenience, Startup Credibility, and Attitude on Online Shopping Intention?

The novelty of this research is the introduction and empirical validation of Internet Accessibility as a vital, context-specific moderator, providing a more accurate theoretical framework for e-commerce adoption in emerging markets.

Research Contribution

The findings of this research offer significant contributions to both theory and practice. Theoretically, this study contributes to resolving the model heterogeneity often observed in online shopping behavior research by incorporating a crucial, yet neglected, moderating variable. Practically, this research provides strategic guidance to MSME policymakers and digital platforms regarding the critical role of network infrastructure and suggests quality-driven strategies necessary to enhance the appeal and performance of online business in a challenging digital landscape.

Literature Review

Theoretical Foundation

The theoretical framework for modeling consumer intention to engage in online shopping is fundamentally anchored in the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). This grand theory represents a synthesis and modification of several foundational behavioral models, including the Technology Acceptance Model (TAM) (Davis, 1989), the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980), and the Theory of Planned Behavior (TPB) (Ajzen, 1991). TAM contributes key constructs such as Perceived Usefulness (POU) and Perceived Ease of Use (PEOU) as direct antecedents of usage intention (Venkatesh & Davis, 1996). The TRA asserts that belief is the primary factor determining an individual's intention to perform a specific action (Chen & Hsu, 2009). Furthermore, the TPB extends the TRA by incorporating Perceived Behavioral Control (PBC) as an additional predictor of intention, specifically addressing criticism that the TRA neglects control factors in real-life settings (Ajzen, 1991). Consequently, UTAUT provides a robust, comprehensive foundation for analyzing online transaction intention from the perspective of technology acceptance.

Research Variables

Online Shopping Convenience (e-Convenience)

Online Shopping Convenience, often termed e-Convenience, is a primary catalyst for the widespread adoption of online purchasing, fundamentally addressing the inherent "gap in time and location" between consumer and retailer (Degeratu et al., 2000; Colwell et al., 2008; Tan et al., 2007). The rapid expansion of eCommerce is largely predicated on the customer's perception of convenience, a context-based concept where advancements in information technology play a crucial role in altering customer perceptions of speed, price, and access to product information (Kotler & Armstrong, 2013). In the digital sphere, traditional service convenience (SERVCON) transforms, and e-Convenience is precisely defined as "the extent to which the customer perceives that the Web site is simple, intuitive, and user-friendly" (Srinivasan et al., 2002). Its strategic importance means e-Convenience is a dominant factor influencing the tendency to access retailer websites (Jayawardhena et al., 2007) and has been systematically investigated for its multi-dimensional nature.

Building on foundational work, researchers have developed comprehensive scales to measure this multi-dimensional construct. Jiang et al. (2013), referencing Berry et al. (2002) and Seiders et al. (2007), provided a validated, five-dimensional scale for online shopping convenience. These dimensions include Access Convenience, which covers flexibility in time, space, web capability, and product availability; Search Convenience, concerning download speed, web design, search capacity, and product classification; Evaluation Convenience, which relates to the clarity of product information, standardization, and price presentation; Transaction Convenience, which encompasses the ease of checkout, payment methods, and price consistency; and Post-Purchase Convenience, addressing product returns, customer protection, and data security. The strategic importance of e-Convenience is further underscored by studies that emphasize features like rich information content (Cyr, 2008), seamless web/app design (Wolfinbarger & Gilly, 2003; Koo et al., 2008), and essential service elements such as interactivity and security (Parasuraman et al., 2005; Yang et al., 2007). Empirical evidence consistently demonstrates that perceived service convenience significantly and positively impacts consumer attitudes and subsequent online shopping intention (Shergill & Chen, 2005; Colwell et al., 2008), with convenience types examined often including access, search, transaction, and cost-saving elements (To et al., 2007; Lakshmi, 2016).

Despite the strong pull of perceived convenience, consumer concerns related to risk and security can significantly deter purchase intention (Brown et al., 2023). A particularly critical issue is security risk, as consumers harbor anxieties about the misuse of personal and financial information during transactions (Federal Trade Commission, 2010; Comegys et al., 2009). This negative perception can be amplified by external factors, such as inadequate regulation or low consumer literacy, particularly in emerging markets (Almousa, 2011). Furthermore, psychological risk, such as the disappointment resulting from poor product quality, can lead to negative consumer attitudes (Huang et al., 2014). Therefore, enhancing platform security and privacy is critical for reinforcing a consumer's perception of convenience, as e-Convenience is only fully realized when the platform provides sufficient security and ease of use (Shukla, 2014). Ultimately, e-Convenience is a dominant antecedent to positive consumer attitude and subsequent Online Shopping Intention, driven by the consumer's desire to save time, cost, and effort (Laksmi, 2018; To et al., 2007). This study adopts a multi-item instrument for convenience based on the core qualities of the online shopping experience, measured by items such as: (1) easy, (2) flexible, (3) reliable, (4) practical, (5) immediate, and (6) accurate.

Startup Credibility and Trust

The concepts of Credibility and Trust are fundamentally interdisciplinary and function as key determinants in the digital commerce landscape (Liu, 2004; Rieh, 2002). Credibility is operationalized as a characteristic that consumers attribute to the seller, the product, and the entire marketplace within an eCommerce setting (Marsh & Dibben, 2003). Defined as the "belief in the source of information" (Fritch & Cromwell, 2002; Metzger, 2007; Sundar, 2008), for emerging startups, credibility represents a value derived from the diligent efforts of its founders and is practically reflected in the customer's perceived ease of searching for desired products (Sheth & Sisodia, 2012).

Trust occupies a pivotal mediating role in online transactions, serving to transform a consumer's positive attitude into a tangible online shopping intention (Gefen & Straub, 2004; Yousafzai et al., 2010). This construct is established during interactions between unfamiliar parties (Pavlou, 2003) and represents the customer's willingness to accept the inherent transactional risk based on favorable expectations regarding future exchange behavior. Subjectively, trust is often conceptualized either as an "opinion or mental image" (Blackwell et al., 2001) or as the accumulated knowledge and inferences a consumer makes about an object (Mowen & Minor, 2002; Kotler & Keller, 2012). It is foundational for developing consumer intention (Chaudhuri & Holbrook, 2001) and must often be built even before the parties directly interact (Bachmann & Zaheer, 2006).

The formation of consumer trust is structured around two critical components: Trusting Belief and Trusting Intention (McKnight et al., 2001). Trusting Belief, which is the conviction that the trusted party possesses characteristics beneficial to the consumer, is built upon three core elements (McKnight et al., 2001): Goodwill, reflecting the seller's proactive willingness to serve consumer interests; Integrity, concerning the conviction of the seller's honesty and consistent adherence to stated agreements; and Competence, relating to the belief in the seller's ability to effectively fulfill consumer needs.

The digital environment poses unique challenges because consumers rarely engage in the full processing of all available information. Consequently, credibility judgments are often formed rapidly, based on easily accessible visual and experiential cues, such as website aesthetics, visual design elements, and the perceived ease of navigation (Fogg et al., 2003; Sundar, 2008; Metzger et al., 2003; Rieh & Danielson, 2007). This emphasis highlights the critical role of website functional design (Hilligoss & Rieh, 2008). This design-based credibility has a direct correlation with consumer loyalty, as elements like an appealing display and quick response times enhance customer retention (Wang & Shaojing, 2010).

Submitting sensitive personal and financial data online necessitates that consumer trust be structured around specific Digital Reputation and Trust Dimensions. Key dimensions that critically influence online purchase intention include Security, which is the consumer's belief in the internet's capacity to securely transmit sensitive information (Chen & Barnes, 2007; Lee & Turban, 2001); Privacy, which is the consumer's confidence regarding the proper handling of their personal data (Chen & Barnes, 2007; Lee & Turban, 2001), where high security and privacy levels are known to positively affect trust; and Reliability, which refers to the firm's dependability, often enhanced by a positive corporate reputation and accumulated past experience (Balasubramanian et al., 2003; Figueiredo, 2000). Furthermore, a positive overall shopping experience acts as a significant determinant of future purchase intention (Bughin, 2011), driven by both emotional and rational factors (Lwin et al., 2007). In the context of online marketing, source credibility is often transferred to recommendation sources, such as product and service reviews from trusted sources (Cheung et al., 2009; Senecal & Nantel, 2004; Fan et al., 2013). Due to the current lack of standardized metrics specifically integrating the startup credibility and trust contexts, a focused study has adopted a set of integrated credibility dimensions encompassing: (1) Trust; (2) Assured; (3) Convincing; (4) Consistency; (5) Transparent; (6) Integrity; and (7) Competent.

Internet Accessibility in Emerging Digital Markets

Internet Accessibility is scientifically defined as the degree of ease with which users can successfully utilize internet services (Evans, 2008; Belson, 2015). In emerging markets, such as Indonesia, a notable disparity exists between the high volume of mobile user traffic and the corresponding efficacy of eCommerce marketing and website functionality (iPrice, 2017). This ease of access and the consumer's inherent technological familiarity are crucial factors that directly influence transaction intention (Doolin et al., 2002). Specifically, the speed of access is particularly important for consumers engaging in the planning phase of online purchases (Jeong & Lambert, 2001; Perdue, 2001). Empirical evidence indicates that enhanced accessibility can generate a positive effect on both consumer attitude and subsequent purchase intention (Keller & Lehmann, 2006) because the final purchase decision is constructed from interactions with the comprehensive and trustworthy features of an eCommerce platform (Kotler, 2000; Zendehdel et al., 2015).

Technological and Infrastructural Challenges

From a technological standpoint, successful eCommerce hinges on accessibility, which encompasses user-friendly technology (Mason & Rennie, 2009) and high-quality website features, including security, privacy, and design (Вйlanger et al., 2002). Despite a significant increase in mobile visits to eCommerce platforms in Southeast Asia (iPrice, 2017), the Indonesian context reveals a considerable gap: high mobile traffic—with peak visits occurring on Saturdays and Sundays—does not correlate with peak transaction times (iPrice, 2017). This suggests an infrastructural and access challenge. The core assertion within this domain is that stable internet accessibility functions as a necessary infrastructural condition that actively moderates the effectiveness of platform-based and psychological constructs, such as Convenience, Credibility, and Attitude, on ultimate consumer intention. Furthermore, prior literature consistently suggests that many popular websites suffer from accessibility issues, often concerning content compliance (Sullivan & Matson, 2000). Website content—which integrates audio, visuals, and video—is critical as it influences the perceived product image, creates a virtual experience (Kaplanidou & Vogt, 2006), and, when functional and interactive, encourages user engagement (Doolin et al., 2002).

Psychological and Contextual Determinants

From a psychological perspective, the ability to access a product is an initial consumer action (Kahneman, 2003) that directly influences consumer attitudes, particularly during the critical pre-choice evaluation process (Kotler, 2000). Accessibility enables consumers to swiftly and efficiently identify desired goods and services (Keller & Lehmann, 2006), and it has been empirically validated to have a significant positive relationship with final purchase intention (Zendehdel et al., 2015). Relevant psychological determinants of this process include stimulus salience, selective attention, and associative activation (Kahneman, 2003). While studies in developed nations sometimes suggest that smartphone access primarily supplements in-store shopping (Wang et al., 2015), the opposite is true for developing countries, where reliable internet access is absolutely crucial for enabling eCommerce (Molla & Licker, 2005; Martнn et al., 2010). Given this context, which focuses on smartphone users with stable and fast 3G and 4G subscriptions, the key dimensions of accessibility developed for rigorous study include: : (1) Affordability; (2) Availability; (3) Speed; (4) Smoothness; and (5) Stability.

Attitude Toward Online Shopping in the Digital Economy

Attitude is conceptualized as a form of preference that fundamentally dictates product choice (Arnould et al., 2002), representing a relatively stable organizational structure of beliefs, feelings, and behavioral tendencies directed toward a specific object (Hogg & Vaughan, 2011). Within consumer psychology, attitude is an evaluative judgment derived from the attributes inherent in a product (Arnould et al., 2002; Brooks et al., 2013; Huitt & Cain, 2005). The formation of a positive attitude is intrinsically linked to the consumer's perception of superior product attributes (Lafferty & Glodsmith, 2005; Oskamp & Schultz, 2005), and it is ultimately determined by underlying beliefs (Agarwal & Sambamurthy, 2002; Kotler & Keller, 2012; Malhotra, 2010), particularly the conviction regarding the product's excellence (Fishbein, 1997). Attitude toward online shopping is specifically defined as the consumer's positive or negative affective evaluation associated with concluding a purchase on the internet (Chiu et al., 2005), and it is a core affective component of behavior, encompassing the emotional interpretation of an object (Brown et al., 2006).

Modeling and Determinants of Consumer Attitude

The consumer purchase decision process is cognitively influenced by perception, motivation, attitude, and belief (Kotler & Armstrong, 2013). Early modeling of attitude and intention successfully incorporated indicators across four classifications: product value, the overall shopping experience, e-Retail service quality, and perceived risk (Jarvenpaa & Todd, 1997). Fundamentally, consumer attitude is a composite structure comprising (1) beliefs, (2) feelings (emotions), and (3) behavioral intentions regarding a marketplace object (Perner, 2010; Fishbein & Ajzen, 1975). Factors that precede and drive attitude formation include personality traits, perceptions, and, crucially, perceived benefits (Cheung & Lee, 2000; Wolfinbarger & Gilly, 2003). Perceived benefit represents the consumer's subjective assessment of the advantages gained from the online shopping experience, such as increased convenience and overall satisfaction (Forsythe et al., 2006; Shobeiri et al., 2014). This understanding is vital, as a positive attitude consistently demonstrates a significant direct impact on online shopping behavior and subsequent purchase decisions (Chai & Pavlou, 2004; George, 2004; Yang et al., 2007). Furthermore, the speed of transaction confirmation in the online context can swiftly generate positive attitudes and boost purchase intention (Shiau & Luo, 2012).

Measurement Framework and Strategic Implications

Attitude is a powerful construct, often functioning as a critical mediator between consumer intention and final behavior (Shwu-Ing, 2003). Given its multi-faceted nature and occasional lack of conceptual consistency across studies (Li & Petrick, 2008; Solomon et al., 2009), the Multi-Attribute Model is adopted for comprehensive measurement (Smith et al., 2008). This model effectively explains the degree of consumer perception toward their online shopping attitude (Hartel et al., 2010) by integrating three key elements: the specific attributes of the attitude object that serve as purchase standards (Alsamydai et al., 2013, 2015), the consumer's beliefs regarding the presence of those attributes (Mandy & Esther, 2008), and the weights that indicate the priority assigned to each attribute (Smith et al., 2008; Loudon & Bita, 2010). In the digital economy, this shift in customer attitude to adopt new, often lower-priced, standardized offerings—often driven by startup innovation—can lead to market disruption (Christensen et al., 2015). Reflecting the prominence of emotional components in consumer behavior (Malhorta, 2007; Mowen & Minor, 2002), the current research emphasizes the affective dimension with measures encompassing: (1) Like; (2) Passionate; (3) Enthusiastic; (4) Addicted; and (5) Happy.

Online Shopping Intention: Conceptual Frameworks and Determinants

Online Shopping Intention (OSI) is conventionally defined as the consumer's "willingness and intention to conduct transactions online" (Pavlou, 2003), encompassing the desire to search, select, and ultimately purchase products via the internet (George, 2004). This construct represents the consumer's readiness to visit an eCommerce site with the explicit goal of making a purchase. Consistent with the foundational Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980), intention is often a more effective measure than actual behavior for accurately gauging consumer perceptions (Sheth & Mittal, 2004). Fundamentally, intention is constructed upon the consumer's subjective perception regarding the attributes and perceived benefits of the product on offer (Mowen & Minor, 2002). Furthermore, consumers value not only the instrumental function of the technology but also the hedonic pleasure, or enjoyment, derived from navigating the eCommerce environment (Heijden & Creemers, 2003).

Theoretical Perspectives on Intention

OSI is rigorously investigated through two primary, yet complementary, theoretical perspectives: the technology-oriented and the trust-oriented view. The Technology Perspective assesses the consumer's cognitive evaluation of the technological interface, such as the website or application, used for online shopping. The primary value of information technology, in this view, is its potential to "lower search costs, evaluate alternatives, and enhance decision quality" (Heijden & Creemers, 2003). Research in this domain frequently leverages the Technology

Acceptance Model (TAM), which posits that Perceived Usefulness (POU) and Perceived Ease of Use (PEOU) are the key drivers of Intention to Use (IU) (Venkatesh & Davis, 1996). The subsequent adoption of the Unified Theory of Acceptance and Use of Technology (UTAUT) confirms the continued salience of POU and PEOU in the modern digital context (Venkatesh et al., 2003).

The Critical Role of Trust and Risk Mitigation

Conversely, the Trust Perspective emphasizes the pivotal role of trust as a "key success factor" in effectively mitigating the inherent risks associated with online transactions (Koufaris & Hampton-Sosa, 2004; Elbeltagi & Agag, 2016). Trust is exceptionally salient in the online context because it directly reduces the "feeling of uncertainty" that arises when products are intangible and the marketplace's credibility is physically unknown (Tan & Thoen, 2001). As the core element determining a person's intention to perform a specific action (Chen & Hsu, 2009), trust is essential for growing consumer confidence (Gefen et al., 2003). Empirical evidence consistently demonstrates that trust, perceived ease of use, usefulness, and enjoyment are all significant predictors of a customer's purchase intention (Chiu et al., 2009).

Holistic Determinants of Online Shopping Intention

Ultimately, OSI is influenced by a complex blend of monetary factors (such as price incentives for existing customers) and non-monetary factors (such as perceived risk for potential customers) (Kim & Gupta, 2009). Features that strategically enhance purchase intent include swift information processing (Seock & Norton, 2007), convenient options like cash on delivery (COD), and secure return policies (Ashwini & Manjula, 2016). Consequently, both trust and perceived risk are consistently confirmed as critical determinants of online shopping intention (Mohammed, 2014). The measurement scale for Online Shopping Intention in this study is based on seven indicators: (1) Will shop online; (2) Want to shop online; (3) Tend to choose online shopping; (4) Willingness to shop online; (5) Interested in shopping online; (6) Flexible interacting with the website/app; and (7) Website/app is useful for buying products.

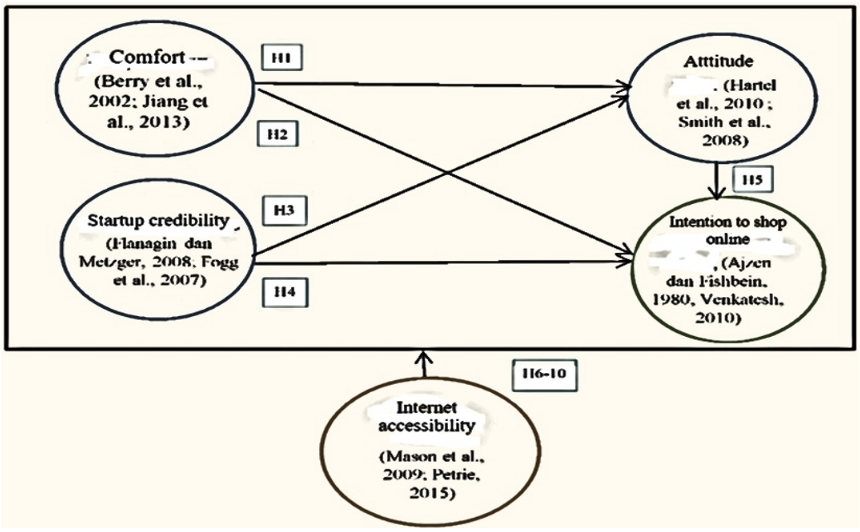

Fig. 1. A proposed model to examine how the relationship between convenience, startup credibility, internet accessibility and positive attitudes and intentions to shop online.

Hypothesis Development

H1: Convenience Positively Affects Attitude Toward Online Shopping

Convenience is a critical service consideration (Seiders et al., 2007) and has a major influence on consumer attitude toward online shopping (As'ad & Ahmad, 2012; Bughin, 2015). The underlying mechanism relies on the consumer's reaction to perceived reality (Drezner, 2002) rather than objective reality. Website factors such as user-friendly design (Srinivasan et al., 2002), ease of navigation, information search, and product selection (Wolfinbarger & Gilly, 2003; Lakshmi, 2016) are central to value creation (Vargo & Lusch, 2004) and lead to positive attitudes (Szymanski & Hise, 2000; Liu et al., 2012). This positive perception of convenience is a strong indicator of a favorable attitude in online transactions (Shah Alam et al., 2008; Lorek, 2010).

H2: Convenience Positively Affects Online Shopping Intention

Convenience, as a form of value exchange in e-business (Vargo & Lusch, 2004, 2008), is consistently identified as a determinant factor for online shopping intention. Previous research highlights several key indicators influencing intention, including website attributes such as ease of navigation (Smith, 2000; Wolfinbarger & Gilly, 2001; Bagdoniene & Zemblyte, 2009), web design (Ranganathan & Ganapathy, 2002), and ease of use (Chen & Hsu, 2009). Other significant convenience factors proven to influence intention include time savings (Karayanni, 2003; Upadhyay & Kaur, 2013), low product price (Ehrt et al., 2007), payment security, privacy protection (Comegys et al., 2009; Smith et al., 2011), and low shipping costs (Teo & Yeong, 2003). These determinant attributes of convenience are consistently and positively linked to online purchase intention (Shah Alam et al., 2008; Lorek, 2010).

H3: Startup Credibility Positively Affects Attitude Toward Online Shopping

Startup credibility is strongly and significantly related to positive consumer attitude and retention (Wang & Shaojing, 2010; Okazaki et al., 2012). Credibility is defined as "trust in the source of information" (Fritch & Cromwell, 2002; Sundar, 2008) and is formed by a cognitive evaluation of visual design elements (Fogg et al., 2003; Metzger et al., 2003) which play a key persuasive role (Petty et al., 2002). Trust is an integral component of credibility (Hardin, 2002; Bachmann & Zaheer, 2006) and is built on the conviction that the purchased product will be beneficial (Mowen & Minor, 2002). In the digital context, key trust dimensions that enhance credibility and shape attitude include security (Kim & Shim, 2002), privacy (Chen & Barnes, 2007), and application reliability (Balasubramanian et al., 2003; Koufaris & Hampton-Sosa, 2004). Collectively, these credibility factors demonstrate a significant capacity to generate a positive attitude toward online shopping.

H4: Startup Credibility Positively Affects Online Shopping Intention

The credibility of a startup and its products helps consumers simplify choices, promises a certain quality, reduces risk, and fosters a sense of security (Mudambi, 2000; Kotler, 2002; Keller, 2003; Keller & Lehmann, 2006). Credibility is essentially "trust in the source" based on perceptions of trustworthiness and expertise, and this positive perception directly influences the intention to purchase (Alhaddad, 2015). When consumers perceive a startup and its offerings as credible, they are more likely to share their experiences and recommend the service to others (Babin et al., 2005; Trusov et al., 2009). This reliance on credible sources and reference groups is critical for online purchase intention (Bansal & Voyer, 2000; Phelps et al., 2004; Bughin et al., 2010). Credibility reflects the consumer's total experience with the product, both before and after purchase (Peres et al., 2010).

H5: Attitude Positively Affects Online Shopping Intention

Attitude, conceptualized as an evaluation of inherent product attributes (Arnould et al., 2002; Brooks et al., 2013), serves to reduce barriers (Schiffman & Kanuk, 2004; Brown &

Venkatesh, 2005; Loudon & Della Bitta, 2010) to a consumer's intention to buy (Fazio, 1990; Fishbein & Ajzen, 1997). A positive attitude is demonstrated by the consumer's belief in the product's superior attributes (Brooks et al., 2013). Since belief is the primary determinant of attitude (Mandy & Esther, 2008; Berkowitz et al., 2003), a strong belief in the product's value and low perceived risk (Overby & Lee, 2006; Yousafzai, 2010) are key factors in translating attitude into online purchase intention (Wu, 2003; Park et al., 2012). The Multi-Attribute Model, which uses attributes, beliefs, and weights, is applied to measure this attitude and its influence on intention (Smith et al., 2008).

H6: The Effect of Convenience on Attitude Toward Online Shopping is Positively Moderated by Internet Accessibility

Customer perception of attributes determines the choice of product and shopping site (Arnould et al., 2005). Favorable perceptions—driven by unique, superior, and reputable attributes (Aaker, 2001; Kotler & Keller, 2012)—contribute to efficiency and convenience (Kotler, 2002) and build consumer loyalty (Kandampully & Suhartanto, 2000). While convenience generates a positive attitude (Keller, 2009; Solomon et al., 2010), Internet Accessibility plays a crucial moderating role. Accessibility represents the consumer's initial action (As'ad & Ahmad, 2012; Bughin, 2015) and involves the cognitive mechanism of intuitive judgment (Kahneman, 2003). Therefore, high accessibility is necessary for the inherent advantages of convenience to be effectively perceived and translated into a positive attitude toward online shopping.

H7: The Effect of Convenience on Online Shopping Intention is Positively Moderated by Internet Accessibility

Convenience allows consumers to search and compare numerous alternatives with low search costs (Childers et al., 2001; Kaufman-Scarborough & Lindquist, 2002), and ease of access has a positive effect on sales (Bagdoniene & Zemblyte, 2009). The strong, positive attitude developed from convenience attributes (Schiffman & Kanuk, 2004; Loudon & Della Bitta, 2010) subsequently influences purchase intention (Fazio, 1990; Fishbein & Ajzen, 1997). Superior product attributes, which offer benefits and security (Kotler, 2002; Aaker, 2004), strengthen this intention (Alhaddad, 2015; Vahid & Aidin, 2012). Internet Accessibility significantly influences this relationship (Zendehdel et al., 2015). High accessibility acts as an enabler, intensifying the link between convenience factors (like efficient searching and low cost) and the ultimate decision to transact (Pavlou, 2003; Morgan & Hunt, 1994), which is fundamentally based on trust and reliability.

H8: The Effect of Startup Credibility on Attitude Toward Online Shopping is Positively Moderated by Internet Accessibility

Consumer attitude is contingent upon the perceived superior attributes of a product, with persuasive and emotional brand aspects helping consumers learn the cognitive and affective elements of a brand (Oskamp & Schultz, 2005; Keller, 2009). Digital marketing and website characteristics—such as being global, open, transparent, and interactive (Dutta, 2009; Stephen & Galak, 2010)—are effective channels for building startup credibility through intensive information sharing and reliable testimonials. However, the initial consumer action is driven by Internet Accessibility (Kahneman, 2003). This accessibility facilitates the intuitive assessment and cognitive response mechanism (Hogg & Banister, 2001) that is essential for leveraging the perceived credibility of the startup and translating it into a positive consumer attitude toward online shopping.

H9: The Effect of Startup Credibility on Online Shopping Intention is Positively Moderated by Internet Accessibility

Startup credibility, which is based on trust and expertise, positively influences product purchase intention (Alhaddad, 2015). When a digital venture and its products are perceived as credible, consumers are more likely to share positive experiences and recommend them (Babin et al., 2005; Trusov et al., 2009). Internet Accessibility—the degree of ease with which users access internet services—is proven to be related to consumer purchase intention (Zendehdel et al., 2015). High accessibility simplifies the process of identifying sellers and products quickly (Keller & Lehmann, 2006). This ease of access encompasses the aggregate features of security, privacy, and usability, which are key to transaction intention. Therefore, a high degree of internet accessibility strengthens the impact of perceived startup credibility on the consumer's intention to transact online.

H10: The Effect of Attitude on Online Shopping Intention is Positively Moderated by Internet Accessibility

Online purchase intention is viewed as a consequence of attitude (Koufaris, 2002), where trust is a salient factor due to the human-computer interaction domain (O`Keefe & Cole, 2000). Consumers are influenced not only by the instrumental value of the technology but also by the hedonic value of visiting an eCommerce site (Heijden & Creemers, 2003). Positive attitude, built from a perceived strong site reputation (Gefen et al., 2003) and attractive virtual experience (Kaplanidou & Vogt, 2006; Doolin et al., 2002), is fundamental to intention. Studies emphasize that speed of access (Jeong & Lambert, 2001; Perdue, 2001) and secure, stable connectivity (Mason & Rennie, 2009) are critical infrastructural factors. High Internet Accessibility is a key determinant (Evans, 2008; Belson, 2015) that enables the smooth, intended engagement with the eCommerce environment, thereby positively moderating the influence of a favorable consumer attitude on the actual intention to shop online.

Fig. 2. Research Location Map.

Research Methodology

The research methodology is designed to provide a clear and structured framework for the instruments used to scientifically test the proposed hypotheses. This chapter details the research scope, sampling technique, operational definitions and variable measurement, and the statistical methods employed.

Research Scope and Context

This study is theoretically anchored in Cognitive Theory, which addresses the individual's ability to acquire and process information, encompassing the stages of perception, attention selection, and memory. The research adopts a consumer behavioral approach, focusing on understanding consumption decisions for the consumer's self-interest.

The study is contextualized within the online shopping landscape of Indonesia, specifically on Java Island. This setting is chosen due to the significant growth in digital adoption: a 2017 survey by the Indonesian Internet Service Providers Association (APJII) reported internet access reached 143.26 million users, with 66% (94,551,600 people) accessing the internet via smartphones. Furthermore, the rapid growth of the eCommerce sector, with 185 companies recorded by 2015 (Mars Research, 2017), and a significant 20% increase in consumer online shopping behavior (Mars Research, 2018) solidify this location's relevance.

The research was conducted in 14 selected metropolitan and secondary cities on Java Island (clustered as Jabodetabek, Joglosemar, and Gerbang Kertosusila), which collectively represent 39% of Java's smartphone users (APJII, 2022). The study uses a cross-sectional survey design to analyze the correlation dynamics between variables.

Sampling Technique

The target population comprises individuals intending to shop online on Java Island. Given the unknown exact distribution of the population, a non-probability sampling technique was utilized. The sample was taken from the selected city clusters (Jabodetabek, Joglosemar, and Gerbang Kertosusila) which are known to have dropship facilities.

The sample was selected based on specific criteria established by the researchers (Baran, 2016):

1. Must be a smartphone user with access to the internet.
2. Must have prior internet usage experience.
3. Must include respondents across four generational categories (McCrindle, 2017): Baby Boomer (aged 53+), Generation X (aged 42–52), Generation Y/Millennial (aged 24–41), and Generation Z (aged 13–23).

The final sample size was determined to be N=720 respondents, satisfying the minimum requirements for correlation and regression analysis (Sekaran, 2006). The calculation was derived using the Ssize formula (Lemeshow et al., 2019) as follows:

Step 1: Initial calculation:

$$n = \frac{3,816 * (0,5 * (1 - 0,5))}{0,1 * 0,1} = 96,04$$

Step 2: Check if the Finite Population Correction (FPC) is applicable. If the initial n calculated above is 10% or more of the size of the majority of the age group, then the FPC can be applied. If the FPC can be applied, then continue with the sample size calculation. If the FPC cannot be applied, then proceed to Step 3 below.

Step 3: Multiplying by the design effect and the estimated age number:

$$n = 96,04 * 1,5 * 4 = 576,24$$

Step 4: Adjusting for expected non-response to obtain the final sample size:

$$n = 576,24 / 0,8 = 720$$

The final sample size of N=720 was distributed proportionally across the survey locations.

Table 1. Population distributed proportionally.

No.	City Cluster	Sample Size (N)
1	Jabodetabek	328
2	Joglosemar	190
3	Gerbang Kertosusila	202
Total		720

Data Collection and Timing

Data was collected using a digital-based questionnaire survey. The research fieldwork was conducted between September and October 2023.

Statistical Data Analysis Technique

The inferential data analysis technique utilized in this study is Partial Least Squares Structural Equation Modeling (PLS-SEM), implemented using the SmartPLS 3 software.

Rationale for Using Partial Least Squares (PLS-SEM)

PLS is a powerful estimation method for structural models that operates with a distribution-free approach, meaning it does not rely on the assumption of data normality. It is particularly effective for handling complex relationships between variables and accommodating smaller sample sizes (Hair et al., 2010).

The key advantages for using PLS in this research include:

1. Robustness to Distribution: It is not limited by the assumption of multivariate normal data distribution, allowing the use of various indicator scales (nominal, ordinal, interval, ratio) within the same model.

2. Model Complexity and Estimation: PLS can estimate models with a large number of latent and manifest variables without encountering data estimation problems.

3. Model Specification: Because the method is focused on maximizing predictive power and uses limited estimation procedures, the influence of model misspecification on parameter estimates is minimized.

4. Indicator Flexibility: It can simultaneously analyze constructs formed by reflective and formative indicators.

5. Data Refinement: PLS-SEM allows for the elimination of inconsistent instrument items using the bootstrapping procedure, which is not feasible in Covariance-Based SEM (CB-SEM) without prior pilot testing and refinement (Ghozali, 2012).

6. Moderator Analysis: PLS-SEM can directly compute and test moderator variables.

PLS-SEM Analysis Steps

The PLS analysis process involves evaluating two sub-models and testing hypotheses using the resampling (Bootstrapping) method to determine statistical significance.

1) Designing the Structural Model (Inner Model)

The Inner Model specifies the relationships between the latent constructs, based on the research hypotheses. The model is evaluated by examining the R2 value for the endogenous variables, which indicates the explanatory power of the model. Path coefficients are estimated using the bootstrapping procedure, where a relationship is deemed significant if the t-statistic is greater than 1.96 (at a 5% significance level) or greater than 1.65 (at a 10% significance level).

2) Designing the Measurement Model (Outer Model)

The Outer Model defines how each block of indicators relates to its corresponding latent variable. This step determines the nature of the indicators (reflective or formative) based on the operational definition of the variable.

3) Conversion of Path Diagram to System of Equations

a. The basic equation model of the Inner Model can be written as follows:

$$\eta = \beta 0 + \beta\eta + \Gamma\xi + \zeta\eta_j + \sum i\beta_{ji}\eta_i + \sum i\gamma_{jb}\xi_b + \zeta_j$$

Information:

η — endogenous latent construct matrix

β — coefficient matrix of endogenous variables

ξ — exogenous latent construct matrix

Γ — exogenous variable matrix coefficients

ζ — inner model residual matrix

b. The basic equation model of the Outer Model can be written as follows:

$$X = \Pi x\xi + \varepsilon x$$
$$Y = \Pi y\eta + \varepsilon y$$

Information:

x dan y — matriks variabel manifes independen dan dependen

ξ dan η — matrix of independent latent constructs and dependent

Π — coefficient matrix (loading matrix)

ε — outer model residual matrix

Estimation of Weights, Path Coefficients, and Loadings

The parameter estimation method in PLS is the Least Squares method. The iterative calculation process estimates three parameters:

1. Weight estimates used to calculate the latent variable scores.
2. Path estimates linking the latent variables and loading estimates linking latent variables to their indicators.
3. Mean and location parameters (regression constant/intercept) for the indicators and latent variables.

Goodness-of-Fit Evaluation

The overall model fit is evaluated using the R2 of the dependent latent variables and the Q2 Predictive Relevance. The Q2 value measures how well the observed values are reconstructed by the model and its parameters. The formula is:

Q2=1−(1−R12)(1−R22)...(1−Rp2)

where R12,R22,...,Rp2 are the R2 values of the endogenous variables. Q2 ranges from 0 to 1, with values closer to 1 indicating better predictive relevance, which is equivalent to the total coefficient of determination in path analysis.

Hypothesis Testing

Hypotheses (paths β, Γ) are tested using the Bootstrapping resampling method, which allows for a distribution-free approach and is not dependent on large sample size assumptions. The t-test statistic is used, and hypotheses are supported if the p−value$\leq$0.05 (or t−statistic>1.96).

Result

Profile of Online Shopping Consumers in Key Urban Areas

The demographic profile of the N=720 respondents highlights an online consumer segment characterized by youth, a female skew, moderate to high education levels, and concentration within major metropolitan areas. The sample exhibited a gender distribution with 57.6% female and 42.4% male participants. Age distribution was overwhelmingly dominated by younger generations, with Generation Z (13–23 years) at 68.8% and Millennials (24–41 years) at 20.1%, collectively accounting for 88.9% of the total sample.

This supports the observation that the Millennial generation "tends to have better education and is keen on online shopping". Conversely, the older demographic (Baby Boomers, 53–69 years) comprised only 4.2% of the sample. In terms of education, the largest segment reported high school graduation (Tamat SMA Sederajat) at 39.3%, followed by Diploma holders at 24.6%, and a significant proportion holding Postgraduate degrees (Tamat Pasca Sarjana) at 21.6%. Regionally, the majority of respondents were domiciled in Jabodetabek (45.6%), with Joglosemar and Gerbang Kertosusila comprising 26.4% and 28.1%, respectively, underscoring the study's focus on these key urban centers.

Mobile Connectivity and Information Sourcing

Analysis of mobile network usage indicates that Telkomsel holds the largest market share among respondents at 45.1%, followed by XL (28.1%) and Indosat Ooredoo (15.5%). This distribution aligns with Telkomsel's established status as a "market leader" with the "widest coverage" and a base of "high-value customers". Given the robust growth of data communication services and the Internet of Things (IoT), the priority for telecommunication operators is undergoing a strategic shift from merely expanding the Total Addressable Market to enhancing service quality. The primary sources for online shopping information distinctly reflect the young demographic's social media usage, with Instagram (50.0%) and Facebook (28.5%) dominating. This pattern confirms the dominant influence exerted by companies owned by Mark Zuckerberg in shaping online consumer information pathways. Furthermore, this high reliance on social media for information is consistent with 2017 APJII research reporting that the majority of internet users are concentrated in the Java region.

Online Purchase Behavior and Platform Preference

The respondents' online shopping behavior is characterized by a distinct set of preferred product categories. These are led by Fashion (32.0%), followed by Cosmetics (22.5%) and Gadgets (22.1%). This finding partially contrasts with a 2016 MARS research report which, while agreeing on the popularity of fashion/clothing (45.8%), listed cosmetics at a much lower 3.5%. In terms of platform preference, the study found that Tokopedia is the most preferred online shopping site, selected by a majority of respondents at 64.9%, followed by Shopee (19.4%) and Lazada (8.1%). This platform ranking generally correlates with findings from the iPrice Indonesia (October 2018) study on the Indonesian eCommerce Map.

Descriptive Statistics of Study Variables

The analysis of descriptive statistics was performed using data obtained from respondent answers to each measuring indicator for the variables under study. It is noted that certain indicators were excluded from the descriptive presentation as they were not utilized in the formal hypothesis testing. The resulting mean scores, which range from 10 to 25, collectively indicate that all variables received high scores, suggesting a generally positive perception across the constructs investigated.

The Accessibility variable, with a theoretical range of 8 to 20, yielded a mean value of 15.61 and a standard deviation of 3.16. The mean score closely approximates the median value of 16, suggesting that respondents perceive ease in accessing the internet. However, the standard deviation of 3.16 indicates a dispersed variability in these perceptions.

The Convenience variable had a theoretical range of 8 to 15, resulting in a mean of 12.91 and a standard deviation of 1.80. With the mean score closely approaching the median of 13, it can be concluded that respondents generally feel comfortable with online shopping. The relatively low standard deviation suggests a homogeneous variability in these responses compared to other variables.

For the Credibility variable, the theoretical range spanned 12 to 25, showing a mean of 18.22 and a standard deviation of 3.07. The mean of 18.22, which is near the median of 19, suggests that respondents agree that the accessed startups are credible.

The Attitude variable's theoretical range was 10 to 25, with a mean score of 19.58 and a standard deviation of 3.37. The mean is close to the median of 20, indicating that respondents possess a positive attitude toward online shopping. Similar to Accessibility, the standard deviation suggests a dispersed variability in these attitudinal responses.

The table below summarizes the descriptive statistics for the five key variables investigated in the study, based on a sample size of N=720.

Table 2. The descriptive statistics.

Variable	N	Minimum	Maximum	Mean	Median	Standard Deviation
Accessibility	720	8	20	15.61	16	3.16
Convenience	720	8	15	12.91	13	1.80
Credibility	720	12	25	18.22	19	3.07
Attitude	720	10	25	19.58	20	3.37
Intention	720	10	30	22.67	23	4.05

Finally, the Intention to shop online variable had the broadest theoretical range of 10 to 30, resulting in the highest mean score of 22.67 and the largest standard deviation of 4.05. The mean value aligns closely with the median of 23, indicating that respondent intention for online shopping is high. However, the substantial standard deviation reveals that the variability in these intentions is highly dispersed. In conclusion, the collective descriptive data demonstrates that respondents hold diverse and varying perceptions regarding the variables examined in this study.

Hypothesis Testing

The significance test in the SEM PLS model aims to determine the influence of exogenous variables on endogenous variables. Hypothesis testing using the SEM PLS method is performed by conducting a bootstrapping process with the aid of the SmartPLS 3.0 computer program, which yields the influence of the exogenous variables on the endogenous variables.

Hypothesis testing is conducted after the structural model evaluation stage. This is done to ascertain whether the proposed hypothesis is accepted or rejected.

— A path coefficient value ranging from -0.1 to 0.1 is considered not significant.

— A coefficient value > 0.1 is considered significant and directly proportional (positive relationship).

— A coefficient value < -0.1 is considered significant and inversely proportional (negative relationship) (Hass and Lehner, 2009).

Table 3. Bootstrapping Calculation Results Mean, STDEV, T-Values, P-Values.

	Sampel Asli (O)	Rata-rata Sampel (M)	Standar Deviasi (STDEV)	T Statistik (|O/STDEV |)	P Values
Accessibility → Convenience	0,549	0,548	0,034	16,172	0,000
Accessibility → Credibility	0,353	0,351	0,037	9,478	0,000
Accessibility → Attitude	0,126	0,128	0,037	3,405	0,001
Accessibility → Intention	0,128	0,129	0,030	4,301	0,000
Convenience → Attitude	0,432	0,431	0,038	11,467	0,000
Convenience → Intention	0,076	0,074	0,031	2,420	0,016
Credibility → Attitude	0,302	0,303	0,031	9,822	0,000
Credibility → Intention	0,258	0,257	0,024	10,642	0,000
Attitude → Intention	0,515	0,516	0,026	19,825	0,000
Moderating Effect of Convenience → Attitude	0,005	0,007	0,031	0,158	*0,874*
Moderating Effect of Credibility → Attitude	0,107	0,105	0,029	3,664	0,000

End of Table 3.

	Sampel Asli (O)	Rata-rata Sampel (M)	Standar Deviasi (STDEV)	T Statistik (|O/STDEV |)	P Values
Moderating Effect of Attitude → Intention	-0,166	-0,165	0,024	6,831	0,000
Moderating Effect of Credibility → Intention	-0,008	-0,009	0,024	0,328	*0,743*
Moderating Effect of Attitude → Intention	0,111	0,111	0,025	4,433	0,000

In addition, to see whether the proposed hypothesis can be accepted or rejected, one can look at the t-statistic value generated from the Path Coefficients output (Mean, STDEV, T-Values).

Using a two-tailed test and an alpha (α) level of 5%, the critical value for rejecting and accepting the proposed hypothesis (the t-table value) is 1.96. If the t-statistic value >1.96, the proposed hypothesis is supported (accepted). Conversely, if the t-statistic value <1.96, the proposed hypothesis is not supported (rejected) (see Table 3).

Results of Direct and Moderating Effects in Online Shopping Behavior

The analysis tested ten hypotheses concerning the direct and moderating effects on consumer attitude and intention toward online shopping, using a significance threshold where hypotheses were supported if the t-statistic exceeded the critical value of 1.96 and the p-value was below 0.05.

Direct Effects on Attitude and Intention

All five direct influence hypotheses (H1 to H5) were statistically supported. Convenience demonstrated a positive and significant influence on both Attitude (t=11.467, p=0.000) and Intention (t=2.420, p=0.016). Quantitatively, the influence of Convenience on Attitude was substantial at 43% (Original Sample Estimate =0.432) , with this positive Attitude being driven by consumer perceptions of ease, flexibility, and practicality. Its influence on Intention, however, was smaller, estimated at 8% (Original Sample Estimate =0.076).

Similarly, Startup Credibility positively and significantly influenced both Attitude (t=9.822, p=0.000) and Intention (t=11.467, p=0.000) , contributing 30% of the influence on Attitude and 26% on Intention. The key indicators of this positive influence are trustworthiness, assurance, consistency, transparency, and integrity. The relationship between Attitude → Intention was the strongest observed, proving highly significant (t=19.825, p=0.000) and accounting for 52% of the total influence on online shopping intention. This powerful effect is fostered by positive affective indicators such as liking, enthusiasm, and excitement toward shopping.

Moderating Role of Internet Accessibility

The moderating role of Internet Accessibility was evaluated following confirmation that all relevant main effects were significant. The results for the moderating hypotheses were mixed. Internet Accessibility did not statistically moderate the relationship between Convenience → Attitude (H6: t=0.158, p=0.874) or the relationship between Startup Credibility → Intention (H9: t=0.328, p=0.743). This lack of moderation suggests that once consumers achieve a sense of comfort or perceive a startup as credible, the issue of accessibility ceases to be a constraint, aligning with findings from prior studies conducted in the Netherlands and the United States.

In contrast, Internet Accessibility emerged as a significant moderator in three instances. It significantly moderated the relationship between Convenience → Intention (H7: t=6.831, p=0.000) , although the empirical moderating influence was observed to be negative at -17%.

Furthermore, it positively moderated the paths from Startup Credibility → Attitude (H8: t=3.664, p=0.000) and Attitude → Intention (H10: t=4.433, p=0.000) , contributing 10% and 11% of the influence, respectively. Notably, for both supported positive moderation effects, the indirect influence of Internet Accessibility through the mediating variable (Startup Credibility → Attitude: 0.344; Attitude → Intention: 0.374) was found to be more effective than its direct influence on the respective endogenous variables (Attitude: 0.126; Intention: 0.128).

Discussion

Consumer Psychographics

This research reveals a unique consumer psychographic dominated by females (57.6%) over males (42.4%). Crucially, the sample is overwhelmingly young, with the majority belonging to Generation Z (68.8%) and Millennials (20.1%) based on McCrindle's (2017) age categories. This composition signifies a notable deviation from prior mainstream reports that were typically dominated by Millennials. The dominance of young female consumers from Generation Z directly aligns with their most common online purchases: fashion/clothing and other products (48.3%), followed distantly by games and other product options (8.8%), and cosmetics and other product options (2.7%). This trend is corroborated by MARS, Incorporated (2017) research, which identified the most frequently purchased online products in Indonesia as clothing (45.8%), accessories (10.9%), shoes (6.7%), and cosmetic products (3.5%).

Online Behavior

Internet Access and Online Shopping Behavior

In terms of Internet access and online shopping behavior, a vast majority of respondents access the internet via smartphones, a finding consistent with the APJII (2019) report that 93.9% of Indonesian internet users utilize smartphones. The most used mobile operator is Telkomsel (41.9%), followed by XL (25.4%) and Indosat Ooredoo (10.4%). Telkomsel's position as the market leader with the widest coverage is significant, as its "high value customers" often act as "influencers that actually trigger a growth in the business customer base." Given the recent surge in data communication services and the Internet of Things (IoT), operators are now shifting their focus from Total Addressable Market to prioritizing service quality.

Online shopping via smartphones is heavily concentrated on Java Island, accounting for 58.08% of users (54,915,570 people). Although Mars Research (2017) indicated a significant 20% increase in online shopping behavior across 30 major Indonesian cities compared to the previous period, current growth remains low. In summary, online shopping is concentrated on Java, albeit with low growth, and is dominated by Generation Z consumers who are generally still dependents of their families.

Online Information Sources and Shopping Platforms

The predominance of Gen Z and Millennials also shapes their use of online information sources and shopping platforms. The key platforms for searching for online shopping information via smartphone are social media, with a staggering 96.9% utilizing these channels, in sharp contrast to interpersonal communication (3.1%). Traditional media (radio, newspapers, television) are no longer primary sources. The top platforms are Instagram (50%), Facebook (28.5%), Twitter (5.7%), and Line (4.4%), which suggests a dominance by companies under Mark Zuckerberg, followed by the South Korean-made platform, Line.

Regarding preferred e-commerce platforms for physical goods, Tokopedia (64.9%) overwhelmingly leads the market, followed by Shopee (19.4%), Lazada (8.1%), and Bukalapak (5.8%). The researchers specifically excluded service platforms like Traveloka, Grab, and GoJek to focus on physical goods. It is noteworthy that Shopee ranked second, aligning with the fact that it was the most aggressive advertiser on television and social media during the study period.

This suggests a direct correlation between its advertising strategy and its ability to draw consumers to the platform. This observation is consistent with the iPrice Indonesia (October, 2018) "Map of E-commerce Indonesia" report, which ranked the major players by average quarterly website visitors, placing Tokopedia first.

The Driving Factors of Online Shopping: Convenience, Credibility, and Attitude

The hypothesis testing results reveal a robust set of relationships among convenience, startup credibility, attitude toward online shopping, and ultimately, online shopping intention. These findings provide a structured understanding of the core factors that influence consumer behavior in the digital marketplace, highlighting both the direct effects of these variables and the crucial moderating role of Internet accessibility.

The Positive Influence of Convenience

The research strongly confirms a significant and positive influence of convenience on attitude toward online shopping. This high positive estimate suggests that the primary constituents of convenience—specifically the ease and practicality of the online purchasing procedure—are instrumental. Enhanced ease facilitates a favorable shift in attitude, which subsequently predicts a change in purchasing behavior. Fundamentally, consumers value convenience for "freedom from temporal and spatial constraints". This benefit is particularly realized in Indonesian regions like Jabodetabek, Joglosemar, and Gerbang Kertosusila, where robust internet infrastructure meets diverse product needs. This aligns with Tan et al. (2007), who proposed that the "gap between needs fulfillment and the availability of internet connection has a direct effect on whether online shopping is adopted or not", and Seiders et al. (2005), who noted that "convenience influences customer evaluation and purchase behavior," underscoring its essential role in customer retention.

The convenience construct, defined by ease, flexibility, and practicality, exerts a positive effect on online shopping attitude. This is corroborated by Srinivasan et al. (2002), who found convenience is realized when customers perceive the "website is simple, intuitive, and user-friendly". In the e-retail domain, convenience-oriented customers have limited time and seek to save time and effort in online purchasing, suggesting a perceptual shift away from the necessity of physical product interaction. However, a cautionary note from Lakshmi (2016) and To et al. (2007) suggests that while online shopping is highly convenient for access, search, and cost efficiency, it is often reported as "less convenient in terms of transactions".

Moving from attitude to action, the analysis revealed that convenience also exerts a positive and significant, yet quantitatively low, influence on online shopping intention. This intention is structurally driven by the convenience construct, encompassing its ease, flexibility, and practicality components. This result supports numerous studies—including those by Shah Alam et al. (2008) and Chen and Hsu (2009)—that collectively found "convenience has a positive influence on consumer intention for online shopping". Specifically, facets such as navigation ease are identified as determinant factors for online shopping intention. Cumulatively, these findings establish that greater convenience is linked to a higher online shopping intention, suggesting that this "individual's action" is materially influenced by convenience. Conversely, a lack of convenience effectively diminishes consumer inclination toward online purchasing.

The Critical Role of Startup Credibility

The testing demonstrated that startup credibility positively influences attitude toward online shopping with a moderate effect size. This favorable attitude is fundamentally shaped by core credibility attributes of the digital startup's services, including transparency, trust, integrity, security, and consistency. This finding supports the academic consensus that "credibility expressed in the form of trust has a positive impact on the attitude and intention to shop in the online market". Conversely, factors indicative of low credibility, such as "misuse of personal data or fraud in online payments," were found to negatively impact both attitude and transaction intention.

The analysis further confirmed a positive and significant direct effect of startup credibility on online shopping intention. This influence is the strongest among the external variables (exceeding accessibility and convenience), serving to reinforce the relationship pattern leading from a positive attitude to an intention to purchase. This outcome harmonizes with previous studies that identified a direct relationship between credibility factors and the intention to purchase. Within the scope of this study, intention is influenced by startup credibility indicators encompassing transparency, trust, integrity, security, and consistency. The concept of trust in the digital world is a stable attribute that encourages the dynamics of interactivity between buyers and sellers. Furthermore, transparency is recognized as a key determinant of consumer online shopping intention. Dimensions of virtual credibility, such as "trust and integrity," have a "key role in online transactions to change attitudes and online shopping intentions". Ultimately, a higher level of startup credibility directly correlates with a higher consumer online shopping intention.

The Power of Attitude on Intention

The final test revealed that attitude has a strong, positive, and significant direct effect on online shopping intention. This effect is further magnified by the reinforcing relationships between accessibility, convenience, and credibility with the core attitude construct. The attitudinal dimensions—including enthusiasm, excitement, liking, addiction, and joy—directly predispose consumer online shopping intention. This supports research stating that "a consumer's positive attitude is not shaken by negative information about the attributes of retail goods offered online". The heightened consumer intention is a product of a combined set of dimensions: buyer-seller interaction, desire to purchase, willingness, and general interest in online retail shopping. Empirical data, such as that from the Indonesian E-commerce Association (2015), highlighted high purchase rates for fashion products, mobile phones, and electronics. The findings also affirm that a digital consumer's positive attitude influences online shopping intentions, with hedonic motivation serving as the most influential factor. Consistently, numerous antecedent studies assert that "consumer attitude has a direct influence on online shopping intention".

The Moderating Role of Internet Accessibility

The research provides nuanced insights into the role of Internet accessibility as a moderator, distinguishing between its effects on attitude and intention.

Moderation on Convenience

The test for the moderating effect of Internet accessibility on the relationship between convenience and attitude toward online shopping indicated that the moderation hypothesis was not supported. The statistical metrics suggested that Internet accessibility does not statistically moderate the effect of convenience on attitude. This implies that for consumers who are already comfortable and positive about online shopping, their Internet accessibility needs are presumed to be met, leading convenience to empirically impact attitude directly. This aligns with studies in developed countries, suggesting that accessibility is no longer a substantial barrier in e-commerce and thus is not a primary consideration.

However, testing the moderating influence of Internet accessibility on the relationship between convenience and online shopping intention yielded a supported hypothesis. The moderation effect was significant, signifying that Internet accessibility effectively moderates the positive relationship between convenience and online shopping intention. This is consistent with Kotler and Armstrong (2013), who stated that the interaction between convenience and intention is influenced by factors facilitated by Internet accessibility, suggesting that information technology is key. In the digital age, accessible internet has shifted the customer's perception away from the need for physical product touch during online transactions, a transformation supported by

Thaler (2015). The merging of convenience and accessibility is key in influencing this intention.

Moderation on Startup Credibility

The moderation test for the influence of Internet accessibility on the relationship between startup credibility and online shopping attitude was significant. This indicates that Internet accessibility statistically and empirically moderates, and specifically strengthens, the effect of startup credibility on online shopping attitude. The indirect effect of Internet accessibility on attitude via startup credibility was notably stronger than its direct effect, suggesting that it is more effective as an indirect influence through this channel. Internet accessibility is thus appropriately classified as a moderator variable in this relationship, consistent with research asserting that credibility can shift based on consumer perception of website access and content.

Conversely, the moderation test for the relationship between startup credibility and online shopping intention was not supported. The statistical metrics indicated that Internet accessibility does not statistically moderate the influence of startup credibility on online shopping intention. This result suggests that the effect of startup credibility on intention is direct; once a segment of consumers perceives a startup as credible, they are less likely to consider other variables, leading to a direct influence on their intention. This is similar to findings in developed countries where satisfactory Internet access is assumed for consumers who deem a startup credible.

Moderation on Attitude

Finally, the test confirmed that the moderation effect of Internet accessibility on the relationship between attitude and online shopping intention was significant. This implies that the inclusion of Internet accessibility as a moderator variable strengthens the effect of consumer attitude on shopping intention. A positive consumer attitude is only effective in driving online shopping intention when smartphone users have easy, smooth, fast, and stable internet connectivity. This finding reflects the reality in the tested regions, where users receive relatively good data communication and IoT services. The link between attitude and intention in online shopping is not always direct, as it is modulated by Internet accessibility. Ease of internet access and technological familiarity are key factors for customer transaction intention.

Despite these positive findings, a paradoxical situation exists in Indonesia: iPrice (2019) reported that high mobile traffic does not proportionally equate to e-commerce marketing activity and site effectiveness, largely due to issues with platform or site accessibility. A gap exists between the time spent accessing shopping sites and the actual online purchases. This gap is evident in the studied regions. This leads to the online-to-offline (O2O) model, where consumers use internet accessibility for searching and paying for goods and services but may still pick up items at a physical store or nearest agent.

Novelty and Limitations

Novelty Values

The core novelty of this study revolves around the strategic role of Internet accessibility. Consumer data derived from accessibility can be leveraged to understand consumer behavior regarding product needs and domicile. For Startups, this accessibility data allows for collaborations with SMEs to provide segment-appropriate goods and optimize inventory to be closer to consumers. Fundamentally, the novelty lies in Internet accessibility serving as a mechanism for the synchronization and synergy of consumer data, ultimately making the buying and selling process more efficient for Indonesian consumers. Unlike the Netherlands, where accessibility guides the online-to-offline (O2O) model, or the US, where it functions primarily as an information tool, in Indonesia, Internet accessibility acts as a determinant for online shopping.

Limitations

This research is subject to several limitations. First, it exclusively reviewed the positive influence of convenience, startup credibility, and attitude on online shopping intention. Previous studies (Chevalier and Mayzlin, 2006; Dellarocas and Narayan, 2006) have indicated that all online consumer reviews are positive, yet consumer perception of products differs across e-commerce sites (Bei et al., 2004), depending on the information developed by marketers (Bailey, 2005). Future research should incorporate the effect of negative reviews and should also focus on the selection of latent variable indicators beyond the moderator. Second, the study focused only on external factors (consumers).

Further research should test a combination of external and internal e-commerce factors, as both influence competitive advantage and industry performance. Third, the non-significant findings—where accessibility did not moderate the relationship between convenience and attitude, or credibility and intention—were likely due to the concentration of respondents in major metropolitan areas (e.g., Jakarta, Semarang, Surabaya), where off-peak accessibility is not a major constraint. These findings may not fully represent sub-urban or rural Indonesian areas. Furthermore, the study treated Internet accessibility as a single variable, not distinguishing between its technological aspects (signal strength, speed, reliability) and its psychological aspects (quality of website information, ease of product identification and transaction). Finally, the respondents were limited to internet users in regions (Jabodetabek, Joglosemar, and Gerbang Kertosusila) with relatively good data and IoT services. While mobile visits to e-commerce sites have increased in Indonesia, a gap remains in network infrastructure and traffic, with peak visits occurring on weekends but transactions remaining low (iPrice, 2017). This suggests that accessibility in Indonesia still presents a gap between site access time and actual online purchase, making the high smartphone user-to-transaction ratio in the studied regions disproportionate. Expanding the scope beyond these well-served areas could enhance the generalizability of the results.

Conclusion

The study identifies Internet accessibility as a key variable acting as a moderator in the online shopping process in Indonesia, although not all moderation hypotheses were supported. In cases where the moderation hypothesis was not supported, it suggests that Internet accessibility is not a constraint on online shopping, indicating adequate accessibility in those specific areas. Conversely, in cases where the hypothesis was supported, accessibility appears to be a constraint, signaling that network coverage and traffic still require attention. Both sets of findings collectively demonstrate that Internet accessibility is a determinant factor in the online shopping process in Indonesia.

Specifically, the online shopping intention—which is influenced by convenience, startup credibility, and attitude, and is moderated by Internet accessibility—within the Jabodetabek, Joglosemar, and Gerbang Kertosusila regions is summarized by the following ten points: Convenience has a significant positive influence on both attitude and intention toward online shopping. Similarly, startup credibility also shows a significant positive influence on both attitude and intention. Finally, a positive shopping attitude significantly and positively affects intention to shop online. Regarding the moderating effects, Internet accessibility does not moderate the relationship between convenience and attitude, suggesting accessibility is more effective as a direct influence on attitude. However, accessibility does moderate the relationship between convenience and intention, and the relationship between startup credibility and positive attitude. Conversely, accessibility does not moderate the relationship between startup credibility and intention, as the startup's credibility directly influences intention. Lastly, accessibility strongly moderates the relationship between positive attitude and online shopping intention, a relationship that is further strengthened by the combined effects of accessibility, convenience, and credibility on attitude toward intention.

Implications

Based on the findings above, the research implications that can be put forward are as follows:

Theoretical and Practical Insights

The research provides a crucial theoretical implication by offering an alternative model that specifically highlights the moderating role of Internet accessibility in consumer behavioral processes during online shopping. This finding underscores that building a positive online shopping attitude and enhancing consumer intention is fundamentally tied to a careful consideration of Internet accessibility, addressing both the consumer psychology aspect and the technological infrastructure that supports the experience.

The theoretical insights translate into clear practical implications for online marketers. Strategies should pivot toward emphasizing startup credibility and convenience to positively influence individual attitude and intention. Given that the main contributions to convenience are ease and practicality, startups must focus on improving specialized services and launching promotional initiatives to build consumer awareness regarding the impact of online transactions. Crucially, marketing activities cannot be one-size-fits-all; they must take into account the level of Internet accessibility in each target region. Furthermore, startups need to make significant investments in mobile risk management. This involves securing the mobile infrastructure, enhancing connectivity to websites, providing simple and engaging applications, and implementing sophisticated data protection schemes to mitigate consumer concerns.

Methodological Contribution

On a methodological level, the study contributes a distinct set of measurement constructs. These constructs are specifically tailored to the Indonesian setting, having been developed and validated within the distinct geographic and socio-economic contexts of the Jabodetabek, Joglosemar, and Gerbang Kertosusila regions. This region-specific tailoring ensures the tools are highly relevant and accurate for future research conducted in similar emerging markets.

Recommendations

Based on the research findings, the following recommendations are provided for future study and practical application: First, given the study's rigorous testing, the concepts established should be developed and re-tested in different contexts to enhance their generalizability. Literature on online consumer behavior should continue to incorporate a third phenomenon in the form of a moderator variable (e.g., Internet accessibility), as its inclusion can provide more comprehensive findings and make the practical application of marketing strategies more beneficial. Internet accessibility, as an extra-systemic variable, is a crucial moderator whose exclusion could lead to biased research findings. For future research, it is highly recommended to separate Internet accessibility into its distinct psychological (consumer perception) and technological (infrastructure) aspects for more specific analysis. Second, the practical application of the Internet accessibility variable in marketing will be highly beneficial for e-commerce, helping to select the correct market segments and tailor promotional content to those consumers. Third, to improve generalizability, the sample should be expanded beyond Jabodetabek, Joglosemar, and Gerbang Kertosusila using either offline or online survey methods.

REFERENCES

Adapa, S. 2013. Electronic retailing of prepared food in Australia. Research and development in E-business through service-oriented solutions. IGI Global, Business Science Reference, pp. 280–292.

Agarwal, R., Sambamurthy, V. 2002. Principles and models for organizing the information technology function. MIS Quarterly Executive 1 (1), 1–16.

Ajzen, I. 1991. The theory of planned behavior. Organizational Behavior and Human Decision Processes 50, 2, 179–211.

Ajzen, I. 2001. Nature and operation of attitudes. Annual Review of Psychology 52, 27–58.

Ajzen, I., Fishbein, M. 1980. Understanding attitudes and predicting social behavior. Prentice-Hall.

Almousa, M. 2011. Perceived risk in apparel online shopping: A multidimensional perspective. Canadian Social Science 7, 2, 23–31.

Alsamydai, M. J., Alnaimi, H. M., Dajani, D. M. 2015. Using Fishbein model to measure individual's attitudes toward electronic communication means. International Journal of Sales & Marketing Management Research and Development 5, 2, 1–18.

As'ad, I., Ahmad, F. 2012. An empirical study of E-commerce implementation among SME in Indonesia. International Journal of Independent Research and Studies 1 (1), 13–22.

Ashwini, N., Manjula, R. 2016. An empirical study on consumers perception towads online shopping. International Journal of Management and Commerce Innovations 3, 2, 1103–1110.

Asosiasi Penyelenggara Jasa Internet Indonesia (APJII). 2022. Profil pengguna internet Indonesia. Puskakom UI-APJII.

Badan Pusat Statistik. 2016. Profil penduduk Indonesia hasil SUPAS 2015.

Bagdoniene, L., Zemblyte, J. 2009. Online shopping motivation factors and their effect on Luthuanian consumers. Economics and Management 1, 1, 1–9.

Bailey, A. A. 2005. Consumer awareness and use of product review websites. Journal of Interactive Advertising 6, 1, 68–81.

Balasubramanian, S., Raghunathan, R., Mahajan, V. 2005. Consumers in a multichannel environment: Product utility, process utility and channel choice. Journal of Interactive Marketing 19, 2, 12–30.

Baran, M. 2016. Mixed methods research for improved scientific study. IGI Global.

Beauchamp, M. B., Ponder, N. 2010. Perceptions of retail convenience for in-store and online shoppers. Marketing Management Journal 20, 2, 49–65.

Bei, L. T., Chen, E. Y. I., Widdows, R. 2004. Consumers' online information search behavior and the phenomenon of search vs. experience products. Journal of Family and Economic Issues 25, 4, 449–467.

Belson, D. 2015. The state of the internet. Akamai Technologies, Inc.

Bourlakis, M., Papagiannidis, S., Fox, H. 2008. E-consumer behaviour: Past, present and future trajectories of an evolving retail revolution. International Journal of E-Business Research 4, 3, 64–76.

Broekhuizen, T., Huizingh, E. 2009. Online purchase determinants: Is their effect moderated by direct experience? Management Research News 32, 5, 440–457.

Brunner, T. A., Stocklin, M., Opwis, K. 2008. Satisfaction, image and loyalty: New versus experienced customers. European Journal of Marketing 42, 10, 1095–1105.

Bughin, J. 2015. Getting a sharper picture of social media's influence. McKinsey Quarterly 3.

Chai, L., Pavlou, P. A. 2004. From ancient to modern: A cross-cultural investigation of electronic commerce adoption in Greece and the United States. Journal of Enterprise Information Management 17, 6, 416–431.

Chan, C. Y., Yazdanifard, R. 2014. How customer perception shape buying online decision. Global Journal of Management and Business Research: e-Marketing 14, 2.

Chang, H. H., Chen, S. W. 2008. The impact of online store environment cues on purchase intention: Trust and perceived risk as a mediator. Online Information Review 32, 6, 818–841.

Chen, Y. H., Hsu, I. 2009. Website attributes that increase customer purchase intention: A conjoint analysis. Journal of Business Research 62, 9, 983–988.

Chiu, C. M., Fang, Y. H., Cheng, H. L., Yen, C. 2013. On online repurchase intentions: Antecedents and the moderating role of switching cost. Human Systems Management 32, 4, 283–296.

Chiu, C. M., Hsu, M. H., Lai, H., Chang, C. M. 2012. Re-examining the influence of trust on online repeat purchase intention: The moderating role of habit and its antecedents. Decision Support Systems 53, 4, 835–845.

Christensen, C. M., Raynor, M., McDonald, R. 2015. What is disruptive innovation. Harvard Business Review.

Colwell, S. R., Aung, M., Kanetkar, V., Holden, A. L. 2008. Toward a measure of service convenience: Multiple-item scale development and empirical test. Journal of Services Marketing 22, 2, 160–169.

Comegys, C., Hannula, M., Vaisanen, J. 2009. Effects of consumer trust and risk on online purchase decision-making: A comparison of Finnish and United States students. International Journal of Management 26, 2, 295–308.

Cryan, M. 2012. Understanding web accessibility from the user's perspective. Social Advocacy and Systems Change Journal 3, 1.

Cyr, D. 2008. Modeling web site design across cultures: Relationships to trust, satisfaction, and e-loyalty. Journal of Management Information Systems 24, 4, 25–54.

Dave, G. 2013. Understanding consumer perception towards brand archetypes for selected brand. International Conference on Technology and Business Management 18, 20.

Dholakia, U. M. 2015. What to do when satisfied B2B customers refuse to recommend you. Harvard Business Review.

Diez-Martin, F. 2018. Where we are: An introduction to business education. Journal of Management and Business Education 1, 1, 1–10.

Dutta, S. 2010. What's your personal strategy. Harvard Business Review.

Emrich, O., Paul, M., Rudolph, T. 2015. Shopping benefits of multichannel assortment integration and the moderating role of retailer type. Journal of Retailing 91, 2, 326–342.

Evans, D. 2008. Social media marketing: An hour a day. Wiley Publisher.

Evers, D. 2003. The rise (and fall?) of national retail planning. Tijdschrift voor Economische en Sociale Geografie 93, 1, 107–113.

Eyers, D. R., Potter, A. T. 2015. E-commerce channels for additive manufacturing: An exploratory study. Journal of Manufacturing Technology Management 26, 3, 390–411.

Foxall, G. 2011. Consumer psychology in behavioural perspective. Beard Books.

Freire, A. P., Fortes, R. P. M., Turine, M. A. S., Paiva, D. M. B. 2008. An evaluation of web accessibility metrics based on their attributes. Proceedings of the 26th Annual ACM International Conference on Design of Communication. ACM, 73–79.

Grewal, D., Levy, M. 2016. Marketing. 5th ed. McGraw-Hill/Irwin.

Haig, W. L. 2008. Credibility based logo design: A new perspective for planning and designing successful company logos. Australian Journal of Business and Social Inquiry 6, 3, 23–41.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., Tatham, R. L. 2010. Multivariate data analysis. 7th ed. Pearson Prentice-Hall.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M. 2017. A primer on partial least squares structural equation modeling. 2nd ed. Sage.

Hand, D. J. 2012. Review of Handbook of partial least squares: Concepts, methods and applications. International Statistical Review 80, 3, 488–489.

Hansen, T., Jensen, J. M. 2009. Shopping orientation and online clothing purchases: The role of gender and purchase situation. European Journal of Marketing 43, 9/10, 1154–1170.

Hartel, C. E. J., Russell-Bennett, R. 2010. Heart versus mind: The functions of emotional and cognitive loyalty. Australasian Marketing Journal 18, 1, 1–7.

Hogg, M. A., Vaughan, G. M. 2011. Social psychology. 6th ed. Pearson Education Limited.

Huang, C. C., Yen, S. W., Liu, C. Y. 2014. The relationship among corporate social responsibility, service quality, corporate image and purchase intention. The International Journal of Organizational Innovation 6, 3.

idEA. 2023. Peluang pemasaran produk lokal melalui digital marketing.

Imran, A., Safwan, N., Rehman, K. 2010. Determinants of consumer retention in cellular industry. Journal of Business Research 71, 515–522.

Indrajit, R. E. 2001. E-Commerce: Kiat dan strategi bisnis di dunia maya. Elex Media Komputindo.

Jensen, R. 2008. Dream society realized. 2nd ed. McGraw-Hill Education - Europe.

Johnson, T. J., Kaye, B. K. 2009. In blog we trust? Deciphering credibility of components of the internet among politically interested internet users. Computers in Human Behavior 25, 1, 175–182.

Kim, D. J., Ferrin, D. L., Rao, R. H. 2008. A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk and their antecedents. Decision Support Systems 44, 2, 544–564.

Kim, B. C., Park, Y. W. 2012. Security versus convenience? An experimental study of user misperceptions of wireless internet service quality. Decision Support Systems 53, 1, 1–11.

Koo, D. M., Kim, J. J., Lee, S. H. 2018. Personal values as underlying motives of shopping online. Asia Pacific Journal of Marketing and Logistics 20, 2, 156–173.

Kotler, P., Keller, K., Ang, H. S., Leong, S. M., Tan, C. T. 2009. Marketing management: An Asian perspective. 5th ed. Prentice Hall.

Kotler, P., Keller, K. L. 2012. Marketing management. 14th ed. Pearson-Prentice Hall.

Lee, S. H., Cotte, J. 2009. Post-purchase consumer regret: Conceptualization and development of the PPCR scale. Advances in Consumer Research 36, 456–462.

Li, X., Petrick, J. F. 2018. Reexamining the dimensionality of brand loyalty: A case of the cruise industry. Journal of Travel & Tourism Marketing 25, 1, 68–85.

Limbu, Y. B., Wolf, M., Lunsford, D. 2012. Perceived ethics of online retailers and consumer behavioral intentions: The mediating roles of trust and attitude. Journal of Research in Interactive Marketing 6, 2, 133–154.

Ling, K. C., Lau, T. C., Long, C., Tan, H. P. 2010. The effects of shopping orientations, online trust and prior online purchase experience toward customers' online purchase intention. Faculty of Accountancy and Management, Universiti Tunku Abdul Rahman.

Loudon, D. L., Bitta, A. J. D. 2010. Consumer behavior, concepts and applications. 4th ed. McGraw-Hill.

Madahi, A., Sukati, I. 2012. The effect of external factors on purchase intention amongst young generation in Malaysia. International Business Research 5, 8, 118–129.

Mangalindan, J. P. 2012. Amazon's recommendation secret. Fortune.

Mandy, M., Tang, T., Esther, P. Y. 2018. Consumer attitude towards mobile advertising, the role of permission. International Academy of Business and Economics Audience 8.

Martin, A., Mazalu, R., Cechich, A. 2010. Supporting an aspect-oriented approach to web accessibility design. Proceedings of the Fifth International Conference on Software Engineering Advances (ICSEA). IEEE, 20–25.

Metzger, M. J., Flanagin, A. J., Medders, R. B. 2010. Social and heuristic approaches to credibility evaluation online. Journal of Communication 60, 3, 413–439.

Moeller, S., Fassnacht, M., Ettinger, A. 2009. Retaining customers with shopping convenience. Journal of Relationship Marketing 8, 4, 313–329.

Muhmin, A. G. 2011. Repeat purchase intentions in online shopping: The role of satisfaction, attitude, and online retailers' performance. Journal of International Consumer Marketing 23, 5, 5–20.

Ogba, E. I., Tan, Z. 2009. Exploring the impact of brand image on customer loyalty and commitment in China. Journal of Technology Management in China 4, 2, 132–144.

Okazaki, S., Li, H., Hirose, M. 2012. Benchmarking the use of QR code in mobile promotion: Three studies in Japan. Journal of Advertising Research 52, 1, 102–117.

Oxford Economic Forecasting. 2019. The impact of the express industry on the global economy. Unpublished report.

Palmer, A. 2010. Customer experience management: A critical review of an emerging idea. Journal of Services Marketing 24, 3, 196–208.

Park, E., Kim, E., Funches, V., Foxx, W. 2012. Apparel product attributes, web browsing, and e-impulse buying on shopping websites. Journal of Business Research 65, 11, 1583–1589.

Perner, L. 2010. Consumer behavior: The psychology of marketing.

Pi, S., Sangruang, J. 2011. The perceived risks of online shopping in Taiwan. Social Behavior and Personality: An international journal 39, 275–286.

Prasad, C., Aryasri, A. 2019. Determinants of shopper behavior in e-tailing: An empirical analysis. Paradigm 13, 1, 73–83.

Raman, T. V., Chen, C. L., Mazzoni, D., Shearer, R., Gharpure, C., DeBoer, J., Tseng, D. 2012. ChromeVox: A screen reader built using web technology. Google Inc.

Rofiq, A., Mula, J. M., Scott, A. 2011. Purchase intention to undertake e-commerce transactions in developing countries: Application of theory of planned behavior in Indonesia. Management and Service Science 1, 4, 12–14.

Saprikis, V., Chouliara, A., Vlachopoulou, M. 2010. Perceptions towards online shopping: Analyzing the Greek university students' attitude. Communications of the IBIMA, 1–13.

Shah Alam, S., Bakar, Z., Ismail, H. B., Ahsan, M. N. 2008. Young consumers online shopping: An empirical study. Journal of Internet Business 5, 81–98.

Sheth, J. N., Sisodia, R. S. 2012. The 4A's of marketing: Creating value for customers, companies and society. Routledge.

Shiau, W., Luo, M. 2012. Factors affecting online group buying intention and satisfaction: A social exchange theory perspective. Computers in Human Behavior 28, 6, 2431–2444.

Shukla, P. 2010. Status consumption in cross-national context: Socio-psychological, brand and situational antecedents. International Marketing Review 27, 108–129.

Smith, J. R., Terry, D. J., Manstead, A. S. R., Louis, W. R., Kotterman, D., Wolfs, J. 2008. The attitude-behavior relationship in consumer conduct: The role of norms, past behavior, and self-identity. The Journal of Social Psychology 148, 3, 311–333.

Smith, H. J., Dinev, T., Xu, H. 2011. Information privacy research: An interdisciplinary review. MIS Quarterly, 35, 4, 989–1016.

Udo, G. J., Bagchi, K. K., Kirs, P. J. 2010. An assessment of customers' e-service quality perception, satisfaction and intention. International Journal of Information Management 30, 6, 481–492.

Vidotto, G., Massidda, D., Noventa, S., Vicentini, M. 2012. Trusting beliefs: A functional measurement study. Psicolygica 33, 575–590.

Yousafzai, S. Y., Foxall, G. R., Pallister, J. G. 2010. Explaining internet banking behavior: Theory of reasoned action, theory of planned behavior, or technology acceptance model? Journal of Applied Social Psychology 40, 5, 1172–1202.

СПИСОК ИСТОЧНИКОВ

Adapa, S. 2013. Electronic retailing of prepared food in Australia. Research and development in E-business through service-oriented solutions. IGI Global, Business Science Reference, pp. 280–292.

Agarwal, R., Sambamurthy, V. 2002. Principles and models for organizing the information technology function. MIS Quarterly Executive 1 (1), 1–16.

Ajzen, I. 1991. The theory of planned behavior. Organizational Behavior and Human Decision Processes 50, 2, 179–211.

Ajzen, I. 2001. Nature and operation of attitudes. Annual Review of Psychology 52, 27–58.

Ajzen, I., Fishbein, M. 1980. Understanding attitudes and predicting social behavior. Prentice-Hall.

Almousa, M. 2011. Perceived risk in apparel online shopping: A multidimensional perspective. Canadian Social Science 7, 2, 23–31.

Alsamydai, M. J., Alnaimi, H. M., Dajani, D. M. 2015. Using Fishbein model to measure individual's attitudes toward electronic communication means. International Journal of Sales & Marketing Management Research and Development 5, 2, 1–18.

As'ad, I., Ahmad, F. 2012. An empirical study of E-commerce implementation among SME in Indonesia. International Journal of Independent Research and Studies 1 (1), 13–22.

Ashwini, N., Manjula, R. 2016. An empirical study on consumers perception towads online shopping. International Journal of Management and Commerce Innovations 3, 2, 1103–1110.

Asosiasi Penyelenggara Jasa Internet Indonesia (APJII). 2022. Profil pengguna internet Indonesia. Puskakom UI-APJII.

Badan Pusat Statistik. 2016. Profil penduduk Indonesia hasil SUPAS 2015.

Bagdoniene, L., Zemblyte, J. 2009. Online shopping motivation factors and their effect on

Luthuanian consumers. Economics and Management 1, 1, 1–9.
Bailey, A. A. 2005. Consumer awareness and use of product review websites. Journal of Interactive Advertising 6, 1, 68–81.
Balasubramanian, S., Raghunathan, R., Mahajan, V. 2005. Consumers in a multichannel environment: Product utility, process utility and channel choice. Journal of Interactive Marketing 19, 2, 12–30.
Baran, M. 2016. Mixed methods research for improved scientific study. IGI Global.
Beauchamp, M. B., Ponder, N. 2010. Perceptions of retail convenience for in-store and online shoppers. Marketing Management Journal 20, 2, 49–65.
Bei, L. T., Chen, E. Y. I., Widdows, R. 2004. Consumers' online information search behavior and the phenomenon of search vs. experience products. Journal of Family and Economic Issues 25, 4, 449–467.
Belson, D. 2015. The state of the internet. Akamai Technologies, Inc.
Bourlakis, M., Papagiannidis, S., Fox, H. 2008. E-consumer behaviour: Past, present and future trajectories of an evolving retail revolution. International Journal of E-Business Research 4, 3, 64–76.
Broekhuizen, T., Huizingh, E. 2009. Online purchase determinants: Is their effect moderated by direct experience? Management Research News 32, 5, 440–457.
Brunner, T. A., Stocklin, M., Opwis, K. 2008. Satisfaction, image and loyalty: New versus experienced customers. European Journal of Marketing 42, 10, 1095–1105.
Bughin, J. 2015. Getting a sharper picture of social media's influence. McKinsey Quarterly 3.
Chai, L., Pavlou, P. A. 2004. From ancient to modern: A cross-cultural investigation of electronic commerce adoption in Greece and the United States. Journal of Enterprise Information Management 17, 6, 416–431.
Chan, C. Y., Yazdanifard, R. 2014. How customer perception shape buying online decision. Global Journal of Management and Business Research: e-Marketing 14, 2.
Chang, H. H., Chen, S. W. 2008. The impact of online store environment cues on purchase intention: Trust and perceived risk as a mediator. Online Information Review 32, 6, 818–841.
Chen, Y. H., Hsu, I. 2009. Website attributes that increase customer purchase intention: A conjoint analysis. Journal of Business Research 62, 9, 983–988.
Chiu, C. M., Fang, Y. H., Cheng, H. L., Yen, C. 2013. On online repurchase intentions: Antecedents and the moderating role of switching cost. Human Systems Management 32, 4, 283–296.
Chiu, C. M., Hsu, M. H., Lai, H., Chang, C. M. 2012. Re-examining the influence of trust on online repeat purchase intention: The moderating role of habit and its antecedents. Decision Support Systems 53, 4, 835–845.
Christensen, C. M., Raynor, M., McDonald, R. 2015. What is disruptive innovation. Harvard Business Review.
Colwell, S. R., Aung, M., Kanetkar, V., Holden, A. L. 2008. Toward a measure of service convenience: Multiple-item scale development and empirical test. Journal of Services Marketing 22, 2, 160–169.
Comegys, C., Hannula, M., Vaisanen, J. 2009. Effects of consumer trust and risk on online purchase decision-making: A comparison of Finnish and United States students. International Journal of Management 26, 2, 295–308.
Cryan, M. 2012. Understanding web accessibility from the user's perspective. Social Advocacy and Systems Change Journal 3, 1.
Cyr, D. 2008. Modeling web site design across cultures: Relationships to trust, satisfaction, and e-loyalty. Journal of Management Information Systems 24, 4, 25–54.
Dave, G. 2013. Understanding consumer perception towards brand archetypes for selected brand. International Conference on Technology and Business Management 18, 20.
Dholakia, U. M. 2015. What to do when satisfied B2B customers refuse to recommend you. Harvard Business Review.
Diez-Martin, F. 2018. Where we are: An introduction to business education. Journal of

Management and Business Education 1, 1, 1–10.
Dutta, S. 2010. What's your personal strategy. Harvard Business Review.
Emrich, O., Paul, M., Rudolph, T. 2015. Shopping benefits of multichannel assortment integration and the moderating role of retailer type. Journal of Retailing 91, 2, 326–342.
Evans, D. 2008. Social media marketing: An hour a day. Wiley Publisher.
Evers, D. 2003. The rise (and fall?) of national retail planning. Tijdschrift voor Economische en Sociale Geografie 93, 1, 107–113.
Eyers, D. R., Potter, A. T. 2015. E-commerce channels for additive manufacturing: An exploratory study. Journal of Manufacturing Technology Management 26, 3, 390–411.
Foxall, G. 2011. Consumer psychology in behavioural perspective. Beard Books.
Freire, A. P., Fortes, R. P. M., Turine, M. A. S., Paiva, D. M. B. 2008. An evaluation of web accessibility metrics based on their attributes. Proceedings of the 26th Annual ACM International Conference on Design of Communication. ACM, 73–79.
Grewal, D., Levy, M. 2016. Marketing. 5th ed. McGraw-Hill/Irwin.
Haig, W. L. 2008. Credibility based logo design: A new perspective for planning and designing successful company logos. Australian Journal of Business and Social Inquiry 6, 3, 23–41.
Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., Tatham, R. L. 2010. Multivariate data analysis. 7th ed. Pearson Prentice-Hall.
Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M. 2017. A primer on partial least squares structural equation modeling. 2nd ed. Sage.
Hand, D. J. 2012. Review of Handbook of partial least squares: Concepts, methods and applications. International Statistical Review 80, 3, 488–489.
Hansen, T., Jensen, J. M. 2009. Shopping orientation and online clothing purchases: The role of gender and purchase situation. European Journal of Marketing 43, 9/10, 1154–1170.
Hartel, C. E. J., Russell-Bennett, R. 2010. Heart versus mind: The functions of emotional and cognitive loyalty. Australasian Marketing Journal 18, 1, 1–7.
Hogg, M. A., Vaughan, G. M. 2011. Social psychology. 6th ed. Pearson Education Limited.
Huang, C. C., Yen, S. W., Liu, C. Y. 2014. The relationship among corporate social responsibility, service quality, corporate image and purchase intention. The International Journal of Organizational Innovation 6, 3.
idEA. 2023. Peluang pemasaran produk lokal melalui digital marketing.
Imran, A., Safwan, N., Rehman, K. 2010. Determinants of consumer retention in cellular industry. Journal of Business Research 71, 515–522.
Indrajit, R. E. 2001. E-Commerce: Kiat dan strategi bisnis di dunia maya. Elex Media Komputindo.
Jensen, R. 2008. Dream society realized. 2nd ed. McGraw-Hill Education - Europe.
Johnson, T. J., Kaye, B. K. 2009. In blog we trust? Deciphering credibility of components of the internet among politically interested internet users. Computers in Human Behavior 25, 1, 175–182.
Kim, D. J., Ferrin, D. L., Rao, R. H. 2008. A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk and their antecedents. Decision Support Systems 44, 2, 544–564.
Kim, B. C., Park, Y. W. 2012. Security versus convenience? An experimental study of user misperceptions of wireless internet service quality. Decision Support Systems 53, 1, 1–11.
Koo, D. M., Kim, J. J., Lee, S. H. 2018. Personal values as underlying motives of shopping online. Asia Pacific Journal of Marketing and Logistics 20, 2, 156–173.
Kotler, P., Keller, K., Ang, H. S., Leong, S. M., Tan, C. T. 2009. Marketing management: An Asian perspective. 5th ed. Prentice Hall.
Kotler, P., Keller, K. L. 2012. Marketing management. 14th ed. Pearson-Prentice Hall.
Lee, S. H., Cotte, J. 2009. Post-purchase consumer regret: Conceptualization and development of the PPCR scale. Advances in Consumer Research 36, 456–462.
Li, X., Petrick, J. F. 2018. Reexamining the dimensionality of brand loyalty: A case of the cruise industry. Journal of Travel & Tourism Marketing 25, 1, 68–85.
Limbu, Y. B., Wolf, M., Lunsford, D. 2012. Perceived ethics of online retailers and consumer behavioral intentions: The mediating roles of trust and attitude. Journal of Research in

Interactive Marketing 6, 2, 133–154.
Ling, K. C., Lau, T. C., Long, C., Tan, H. P. 2010. The effects of shopping orientations, online trust and prior online purchase experience toward customers' online purchase intention. Faculty of Accountancy and Management, Universiti Tunku Abdul Rahman.
Loudon, D. L., Bitta, A. J. D. 2010. Consumer behavior, concepts and applications. 4th ed. McGraw-Hill.
Madahi, A., Sukati, I. 2012. The effect of external factors on purchase intention amongst young generation in Malaysia. International Business Research 5, 8, 118–129.
Mangalindan, J. P. 2012. Amazon's recommendation secret. Fortune.
Mandy, M., Tang, T., Esther, P. Y. 2018. Consumer attitude towards mobile advertising, the role of permission. International Academy of Business and Economics Audience 8.
Martin, A., Mazalu, R., Cechich, A. 2010. Supporting an aspect-oriented approach to web accessibility design. Proceedings of the Fifth International Conference on Software Engineering Advances (ICSEA). IEEE, 20–25.
Metzger, M. J., Flanagin, A. J., Medders, R. B. 2010. Social and heuristic approaches to credibility evaluation online. Journal of Communication 60, 3, 413–439.
Moeller, S., Fassnacht, M., Ettinger, A. 2009. Retaining customers with shopping convenience. Journal of Relationship Marketing 8, 4, 313–329.
Muhmin, A. G. 2011. Repeat purchase intentions in online shopping: The role of satisfaction, attitude, and online retailers' performance. Journal of International Consumer Marketing 23, 5, 5–20.
Ogba, E. I., Tan, Z. 2009. Exploring the impact of brand image on customer loyalty and commitment in China. Journal of Technology Management in China 4, 2, 132–144.
Okazaki, S., Li, H., Hirose, M. 2012. Benchmarking the use of QR code in mobile promotion: Three studies in Japan. Journal of Advertising Research 52, 1, 102–117.
Oxford Economic Forecasting. 2019. The impact of the express industry on the global economy. Unpublished report.
Palmer, A. 2010. Customer experience management: A critical review of an emerging idea. Journal of Services Marketing 24, 3, 196–208.
Park, E., Kim, E., Funches, V., Foxx, W. 2012. Apparel product attributes, web browsing, and e-impulse buying on shopping websites. Journal of Business Research 65, 11, 1583–1589.
Perner, L. 2010. Consumer behavior: The psychology of marketing.
Pi, S., Sangruang, J. 2011. The perceived risks of online shopping in Taiwan. Social Behavior and Personality: An international journal 39, 275–286.
Prasad, C., Aryasri, A. 2019. Determinants of shopper behavior in e-tailing: An empirical analysis. Paradigm 13, 1, 73–83.
Raman, T. V., Chen, C. L., Mazzoni, D., Shearer, R., Gharpure, C., DeBoer, J., Tseng, D. 2012. ChromeVox: A screen reader built using web technology. Google Inc.
Rofiq, A., Mula, J. M., Scott, A. 2011. Purchase intention to undertake e-commerce transactions in developing countries: Application of theory of planned behavior in Indonesia. Management and Service Science 1, 4, 12–14.
Saprikis, V., Chouliara, A., Vlachopoulou, M. 2010. Perceptions towards online shopping: Analyzing the Greek university students' attitude. Communications of the IBIMA, 1–13.
Shah Alam, S., Bakar, Z., Ismail, H. B., Ahsan, M. N. 2008. Young consumers online shopping: An empirical study. Journal of Internet Business 5, 81–98.
Sheth, J. N., Sisodia, R. S. 2012. The 4A's of marketing: Creating value for customers, companies and society. Routledge.
Shiau, W., Luo, M. 2012. Factors affecting online group buying intention and satisfaction: A social exchange theory perspective. Computers in Human Behavior 28, 6, 2431–2444.
Shukla, P. 2010. Status consumption in cross-national context: Socio-psychological, brand and situational antecedents. International Marketing Review 27, 108–129.
Smith, J. R., Terry, D. J., Manstead, A. S. R., Louis, W. R., Kotterman, D., Wolfs, J. 2008. The attitude-behavior relationship in consumer conduct: The role of norms, past behavior, and self-identity. The Journal of Social Psychology 148, 3, 311–333.
Smith, H. J., Dinev, T., Xu, H. 2011. Information privacy research: An interdisciplinary

review. MIS Quarterly, 35, 4, 989–1016.
Udo, G. J., Bagchi, K. K., Kirs, P. J. 2010. An assessment of customers' e-service quality perception, satisfaction and intention. International Journal of Information Management 30, 6, 481–492.
Vidotto, G., Massidda, D., Noventa, S., Vicentini, M. 2012. Trusting beliefs: A functional measurement study. Psicolygica 33, 575–590.
Yousafzai, S. Y., Foxall, G. R., Pallister, J. G. 2010. Explaining internet banking behavior: Theory of reasoned action, theory of planned behavior, or technology acceptance model? Journal of Applied Social Psychology 40, 5, 1172–1202.

INFORMATION ABOUT AUTHORS / ИНФОРМАЦИЯ ОБ АВТОРАХ

MULJONO Wiryanta – Research Director.
E-mail: wiryantamuljono@gmail.com
МУЛДЖОНО Вирьянта – директор по исследованиям.
E-mail: wiryantamuljono@gmail.com
ORCID: https://orcid.org/0000-0001-8679-7767

SETIYAWATI Sri – associate professor.
E-mail: srisetiyawati84@gmail.com
СЕТИЯВАТИ Шри – доцент.
E-mail: srisetiyawati84@gmail.com

SETYANTO Padmanabha Adyaksa – Data Analyst.
E-mail: padmanabhaadyaksasetyanto@gmail.com
СЕТЬЯНТО Падманабха Адьякса – аналитик данных.
E-mail: padmanabhaadyaksasetyanto@gmail.com

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PREDICTING CLAIMS IN AUTO INSURANCE USING DEEP NEURAL NETWORKS

Andrei Klimentov ✉

Peter the Great St. Petersburg Polytechnic University, St. Petersburg, Russia

✉ andreiklimentov361@gmail.com

Abstract. In the modern world, the insurance market is subject to significant changes, including under the influence of the use of digital technologies and the introduction of machine learning methods in insurance scoring. The object of the study is a data set with records of insurance policies. The study uses a deep nonlinear neural network to predict the occurrence of claim loss on auto insurance policies. Before using a multilayer neural network, data is pre-processed, and possible data leakage is eliminated. At the output of the neural network model, the resulting loss probability value is converted to a binary value. The model is evaluated using the ROC-AUC metric, with a graph of the ROC curve. The results show that the obtained model has predictive accuracy, but not high enough accuracy for industrial applications of the chosen model. The findings indicate the need for further research on ways to solve this problem using other machine learning methods.

Keywords: machine learning, neural networks, insurance scoring, prediction of insurance events, auto insurance, ROC-AUC, classification, scoring

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ПРОГНОЗИРВОАНИЕ УБЫТКА В АВТОСТРАХОВАНИИ С ИСПОЛЬЗОВАНИЕМ МНОГОСЛОЙНЫХ НЕЙРОННЫХ СЕТЕЙ

Андрей Климентов ✉

Санкт-Петербургский политехнический университет Петра Великого,
Санкт-Петербург, Россия

✉ andreiklimentov361@gmail.com

Аннотация. В современном мире страховой рынок подвержен значительным изменениям в том числе под влиянием применения цифровых технологий и внедрения методов машинного обучения в стразовой скоринг. Объектом исследования является набор данных с записями о страховых полисах. В исследовании используется многослойная нелинейная нейронная сеть для предсказания наступления убытка по полисам автострахования. Перед использованием многослойной нейронной сети проводится предварительная обработка данных, устранение возможны утечек данных. На выходе модели нейронной сети получаемое значение вероятности убытка преобразуется в бинарное значение. Оценка модели проводится по метрике ROC-AUC, с построением графика ROC кривой. Результаты показывают, что полученная модель имеет предсказательную, но недостаточно высокую точность для промышленного применения выбранной модели. Выводы указывают на необходимость дальнейшего исследования способов решения поставленной задачи при помощи других методов машинного обучения.

Ключевые слова: машинное обучение, нейронные сети, страховой скоринг, прогнозирование страховых событий, автострахование, ROC-AUC, классификация, тарификация

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Introduction

In the modern world, the insurance market is subject to significant changes, including under the influence of the use of digital technologies. In particular, machine learning methods are actively used in insurance to solve various problems. The main tasks are to calculate the cost of insurance policies based on the assessment of the client's riskiness and forecasting claim losses. These methods are also actively used to counter fraud (Zabavin, 2009; Vorobyev, 2024; Ignatiev, Levina, 2024).

Thus, according to the data of the Central Bank of Russia for 2024 and the first quarter of 2025, the growth rate of insurance premiums year-on-year exceeds 100% (Bank of Russia, 2025). Such an increase may be due to the widespread introduction of machine learning technologies for assessing insurance policy risks (Makarenko, 2020), as well as calculating insurance premiums.

Scoring is commonly referred to as an automated mathematical scoring system that can be used to assess a client's solvency, for example in the banking sector. In insurance, scoring models can be used to determine the degree of risk in insurance based on multifactor models. For example, in auto insurance, scoring models often use the age of persons allowed to drive a vehicle (TS), as well as the power of the vehicle (Southwell, 2008).

Modern scoring systems based on ML algorithms make it possible to take into account complex nonlinear dependencies, use a wide range of data, including behavioral and external sources, and dynamically adapt to changing market conditions.

The relevance of using machine learning methods in calculating insurance premiums and predicting risks lies in their adaptability and the ability to detect nonlinear dependencies in a large amount of data.

Linear regression models (Varghese and Dash, 2012) and decision tree models (Breima, 2001; Salzberg, 1994) have become the most widespread in insurance scoring systems. However, these groups of methods have limitations that reduce their effectiveness. Thus, logistic regressions often have insufficient accuracy, especially when it comes to nonlinear dependencies or regression parameters are subject to multicollinearity (Kuznetsova, 2015). In turn, a group of machine learning methods based on decision trees are susceptible to overfitting (Karamazin, 2024; Salzberg 1994), and also have a low ability to scale, since when the system or data changes, the model must be completely rebuilt.

Ensemble models, especially those based on boosting, are also widely used. Boosting allows you to create models that consist of simple models combined sequentially, which reduces the errors of each model (Chen and Guestrin, 2016; Diana et al., 2019).

At the same time, boosting models are subject to the problem of class imbalance, complexity of configuration, and poor adaptability to sudden changes (Averro et al., 2023; Coskun and Turanli, 2023).

In addition, neural networks are used, but currently their use in scoring models is limited. Thus, it is of interest to conduct a study aimed at exploring the possibility of using neural networks to predict an insurance event, as well as to evaluate the quality of such models.

In this paper several research questions will be observed. First of all, it will be researched whether multilayer neural networks with nonlinear activation functions will be effective method for insurance events (claims) prediction. Secondly, the level of predictive accuracy by ROC-AUC metric, which can be achieved with this method, will also be question of research. Moreover, advantages and disadvantages of neural network approach to the vehicle insurance will be observed in this work. Furthermore, the possibility of practical applications of deep neural networks will be considered.

Materials and Methods

There is great variability in machine learning methods which are taken into account for dealing with insurance claim prediction. Firstly, models based on decision trees are wide spread and were used in works

The research in this paper will be conducted on the basis of a dataset (Segura-Gisbert et al., 2023) from the Kaggle repository, which characterizes the database of an auto insurance company.

The advantage of the set (Segura-Gisbert et al., 2023) is a large set of attributes, which will allow you to select only the most significant ones due to exploratory data analysis. In addition, a large number of records in the dataset will allow it to be divided into training and verification samples.

For further work, preliminary data processing was carried out. First of all, the parameters were extracted from the time attributes, so, for example, the length of service attribute in numeric format can be obtained from the "date of receipt of the driver's license" attribute. Further, categorical features were also processed, as this is a prerequisite for their inclusion in the neural network model (Valiullin, 2017; Barkov and Senotova, 2021). For encoding, the method of encoding by the name of the feature class (Label Encoding) was applied. Other temporary attributes were also removed after that.

Also, one of the most important aspects in the pre-processing of the data was the removal of the features 'N_claims_year', 'Cost_claims_year', 'N_claims_history', which determine the number of claims under the policy, and the amount of claims. The removal of these features is necessary, as they will create a data leakage when training a neural network model.

An additional loss attribute ('claim_prob') was formed as a predicted feature, which is determined binarily (equal to 1 if there was a loss and 0 if there was no loss).

In addition, the data set is divided into training and test samples. The separation was made in the ratio of 80% of the data included in the training sample, and 20% in the test sample.

Thus, the classification task is set to predict the occurrence of a loss {0,1}. The number of regressors in this task is 14, which requires the use of a deep neural network.

Next, the architecture of the machine learning model was defined. A multilayer neural network with nonlinear activation functions will be used to predict the probability of an insurance event. The ReLU activation function will be used on the input and hidden layers of the neural network, which looks like:

$$ReLU(x) = \max(0, x) = \begin{cases} x, if \ x \geq 0 \\ 0, if \ x < 0' \end{cases} \tag{1}$$

where x – variable on the input of the neuron.

According to (Dubey et al. 2021), this activation function allows solving the problem of decaying gradients and is the standard choice for most tasks solved using neural networks.

The sigmoid activation function (2) will be used on the output layer, which allows you to project the values of the output variable to the interval [0,1], which corresponds to the problem being solved.

$$Sigmoid(x) = \frac{1}{1+e^{-x'}} \tag{2}$$

The mathematical description of the inner layers of a neural network can be represented as (3) according to (Blier-Wong et al. 2020).

$$\begin{gathered} h_j = ReLU(z_j),\ j = 1,...,J \\ z_j = \sum_{k=1}^{14} \omega_{kj} x_{ik} + b_j,\ j = 1,...,J \end{gathered} \tag{3}$$

where J is the width of the hidden layer, g is the activation function, x_ik are the input parameters of the model, i is the observation number, and p is the number of input variables.

The next part is to select the number of hidden layers and the number of neurons on them. According to (Aziz et al. 2024), there is no universal algorithm for selecting the number of hidden layers and neurons per layer. Thus, you can be guided by empirical experience, and you can vary the parameters during experiments.

The quality of the neural network model will be evaluated using a standard metric for the classification problem ROC-AUC. Thus, according to (Stern 2021), the ROC curve shows the ratio of true positive results and false positive results at different risk thresholds. In turn, the AUC area under the ROC curve can be calculated using the formula (4).

$$AUC = \int_0^1 \left(\frac{(1-r)f(r)}{1-r_{mean}} \right) \left(\int_r^1 \frac{xf(x)}{r_{mean}} dx \right) dr \tag{4}$$

where x is an artificial variable for integration, r is the probability of an object belonging to a positive class, $f(r)$ is a probability density function, and r_{mean} is the mathematical expectation of an object belonging to a class.

The advantages of using this metric are its invariance to class imbalance, as well as statistical stability (Richardson et al. 2023).

Results

During the experiments, the best classification accuracy values for the ROC-AUC metric were obtained with the following neural network configuration and represented on Fig. 1.

Fig. 1. The view of neural network architecture.

In the process of training the model on the training sample, the saturation level of the model was determined, after which an increase in the number of training epochs does not significantly affect the accuracy of the model. The training schedule for the model is shown on Fig. 2.

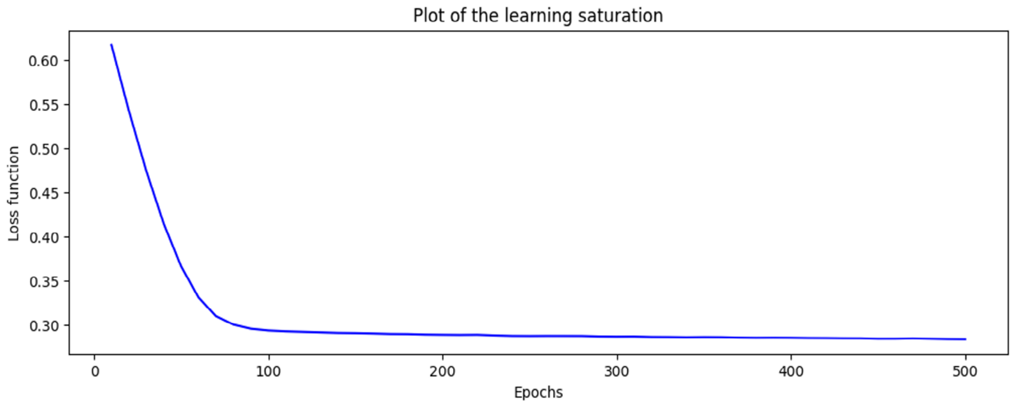

Fig. 2. The plot of the dependence of the model's loss function on the learning epoch.

The graph shows that after 300 epochs, an increase in their number does not significantly affect the accuracy of the model. After training the model, the model was validated on a test dataset. The value of the ROC-AUC metric was also obtained (see Fig. 3).

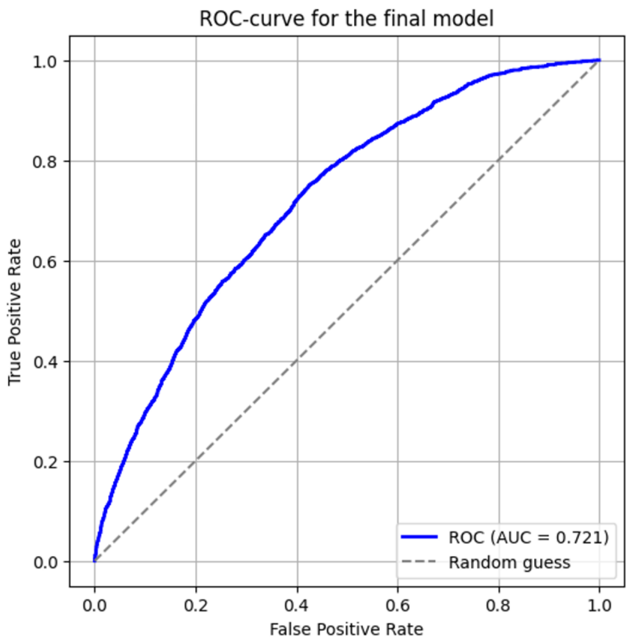

Fig. 3. The plot of ROC curve for the final model.

The exact value of the ROC-AUC metric was 0.72. A model with a similar metric value can be classified as a model that has predictive power and value, but is not optimal.

Thus, the use of multilayer neural networks with nonlinear activation functions makes it possible to solve the problem of predicting the occurrence of an insurance event. In addition, this approach allows you to use the output value of the neural network, which is the probability of an insurance event, when charging the cost of the policy.

Conclusion

In this paper, we investigated the use of a neural network with nonlinear activation functions to solve the binary classification problem in predicting the occurrence of loss.

A distinctive feature of this study is the use of deep neural networks as opposed to methods based on decision trees such as random forest or boosting methods. Moreover, approach with neural networks is not a standard practice in insurance industry due to its low interpretability. As a result, this research allows to evaluate nonstandard approach and make decision whether it is useful to apply it in industry.

The resulting neural network model has predictive power, but it is not accurate enough for industrial applications.

The advantage of using a neural network is that even in the classification task, its output value takes values in the range from 0 to 1, which can be used as the probability of a loss on the policy. This discretized value can be used more flexibly in insurance billing than a discrete value of 0 or 1. Thus, this solution has high prospects for use in the billing of auto insurance policies.

However, the accuracy of the neural network model is not high enough for it to have industrial applications, so other machine learning models should be further explored to solve this problem.

As a result, considering the research questions which are stated in introduction following conclusions could be made. The deep neural network with nonlinear activation functions is not as effective as it was expected because the value of ROC-AUC metric does not exceed 0.72. re are several Thus, the practical application of deep neural networks in auto insurance seems to be bounded due to its average evaluation results.

This is main disadvantage of this approach which was observed in this research. On the other hand, there are several advantages of this method, such as nonlinear dependencies prediction, which are also observed in this paper.

REFERENCES

Averro N., Murfi H., Ardaneswari G. 2023. The Imbalance Data Handling of XGBoost in Insurance Fraud Detection. Science and Technology Publications, 460–467.

Aziz A., Khan T., Iftikhar U., Tanoli I., Qureshi A.K. 2024. Appropriate Selection for Numbers of neurons and layers in a Neural Network Architecture: A Brief Analysis. Sir Syed University Research Journal of Engineering & Technology, 2 (13).

Batten J. A., Ciner C., Lucey B. M. 2008. The Macroeconomic Determinants of Volatility in Precious Metals Markets. SSRN Electronic Journal.

Barkov D., Senotova S. 2021. Encoding of categorial features in neural networks. Scientific Papers Collection of the Angarsk State Technical University 1, 3–8.

Blier-Wong C., Cossette H., Lamontagne L., Marceau E. 2020. Machine Learning in P&C Insurance: A Review for Pricing and Reserving. Risks 1 (9), 4.

Breiman L. 2001. Random forests.

Chen T., Guestrin C. 2016. XGBoost: A Scalable Tree Boosting System, 785–794.

Cohen G. 2022. Algorithmic Strategies for Precious Metals Price Forecasting. Mathematics 7 (10), 1134.

Coskun S. B., Turanli M. 2023. Credit risk analysis using boosting methods. Journal of Applied Mathematics, Statistics and Informatics 1 (19), 5–18.
Diana A., Griffin J. E., Oberoi J. 2019. Machine-Learning Methods for Insurance Applications. Schaumburg, Illinois: Society of Actuaries.
Dubey S. R., Singh S. K., Chaudhuri B. B. 2021. Activation Functions in Deep Learning: A Comprehensive Survey and Benchmark.
Hansen B. E. 2005. Challenges for econometric model selection. Econometric Theory, 1 (21).
Ignatiev P., Levina A. 2024. Artificial intelligence and artificial neural networks in healthcare. Technoeconomics 3, 4 (11), 28–41. DOI: https://doi.org/10.57809/2024.3.4.11.3
Karmazin A. R. 2024. Comparative analysis of the efficiency of various scoring models in factoring.
Kuznetsova I. S. 2015. Problems of multicollinearity in regression models, 3.
Makarenko E. A. 2020. Application of computer scoring in the risk assessment system in property insurance.
Richardson E., Trevizani R., Greenbaum J.A., Carter H., Nielsen M., Peters B. 2024. The receiver operating characteristic curve accurately assesses imbalanced datasets. Patterns 5, 6, 100994.
Salzberg S. L. 1993. Review of C4.5: Programs for Machine Learning by J. Ross Quinlan. Machine Learning 3 (16), 235–240.
Segura-Gisbert J., lledo Benito J., Pavia J. 2023. Dataset of an actual motor vehicle insurance portfolio. doi: 10.21203/rs.3.rs-3631821/v1.
Stern R. H. 2021. Interpretation of the Area Under the ROC Curve for Risk Prediction Models.
Southwell W. 2008. Increasing profitability in a market with tariff competition, 1.
Valiullin A. M. 2017. Preprocessing of categorical features in machine learning problems [In Russ.] In: Robotics and Artificial Intelligence: Proceedings of the IX All-Russian Scientific and Technical Conference with International Participation, 154–157.
Varghese A. A., Dash M. 2012. A Linear Pricing Model for Life Insurance Policies. SSRN Electronic Journal.
Vorobyev I. A. 2024. ML methods for assessing the risk of fraud in auto insurance // Izvestiya of Saratov University. Mathematics. Mechanics. Informatics. 4 (24), 619–628.
Zabavin D. V. 2009. Application of scoring systems to counter crimes in the insurance sphere.
Bank of Russia. 2025. Statistics. URL: https://cbr.ru/insurance/reporting_stat/ (date of access: 13.10.2025).

СПИСОК ИСТОЧНИКОВ

Averro N., Murfi H., Ardaneswari G. 2023. The Imbalance Data Handling of XGBoost in Insurance Fraud Detection. Science and Technology Publications, 460–467.
Aziz A., Khan T., Iftikhar U., Tanoli I., Qureshi A.K. 2024. Appropriate Selection for Numbers of neurons and layers in a Neural Network Architecture: A Brief Analysis. Sir Syed University Research Journal of Engineering & Technology, 2 (13).
Batten J. A., Ciner C., Lucey B. M. 2008. The Macroeconomic Determinants of Volatility in Precious Metals Markets. SSRN Electronic Journal. 2008.
Barkov D., Senotova S. 2021. Encoding of categorial features in neural networks. Scientific Papers Collection of the Angarsk State Technical University 1, 3–8.
Blier-Wong C., Cossette H., Lamontagne L., Marceau E. 2020. Machine Learning in P&C Insurance: A Review for Pricing and Reserving. Risks 1 (9), 4.
Breiman L. 2001. Random forests.
Chen T., Guestrin C. 2016. XGBoost: A Scalable Tree Boosting System, 785–794.
Cohen G. 2022. Algorithmic Strategies for Precious Metals Price Forecasting. Mathematics 7 (10), 1134.
Coskun S. B., Turanli M. 2023. Credit risk analysis using boosting methods. Journal of Applied Mathematics, Statistics and Informatics 1 (19), 5–18.

Diana A., Griffin J. E., Oberoi J. 2019. Machine-Learning Methods for Insurance Applications. Schaumburg, Illinois: Society of Actuaries.

Dubey S. R., Singh S. K., Chaudhuri B. B. 2021. Activation Functions in Deep Learning: A Comprehensive Survey and Benchmark.

Hansen B. E. 2005. Challenges for econometric model selection. Econometric Theory, 1 (21).

Ignatiev P., Levina A. 2024. Artificial intelligence and artificial neural networks in healthcare. Technoeconomics 3, 4 (11), 28–41. DOI: https://doi.org/10.57809/2024.3.4.11.3

Кармазин А. Р. 2024. Сравнительный анализ эффективности различных скоринговых моделей в факторинге.

Кузнецова И. С. 2015. Проблемы мультиколлинеарности в регрессионных моделях, 3.

Макаренко Е. А. 2020. Применение компьютерного скоринга в системе оценки рисков в страховании имущества.

Richardson E., Trevizani R., Greenbaum J.A., Carter H., Nielsen M., Peters B. 2024. The receiver operating characteristic curve accurately assesses imbalanced datasets. Patterns 5, 6, 100994.

Salzberg S. L. 1993. Review of C4.5: Programs for Machine Learning by J. Ross Quinlan. Machine Learning 3 (16), 235–240.

Segura-Gisbert J., lledo Benito J., Pavia J. 2023. Dataset of an actual motor vehicle insurance portfolio. doi: 10.21203/rs.3.rs-3631821/v1.

Stern R. H. 2021. Interpretation of the Area Under the ROC Curve for Risk Prediction Models.

Саузвел У. 2008. Увеличение прибыльности на рынке с тарифной конкуренцией, 1.

Валиуллин А. М. 2017. Предобработка категориальных признаков в задачах машинного обучения. Робототехника и искусственный интеллект : Материалы IX Всероссийской научно-технической конференции с международным участием, 154–157

Varghese A. A., Dash M. 2012. A Linear Pricing Model for Life Insurance Policies. SSRN Electronic Journal.

Vorobyev I. A. 2024. ML methods for assessing the risk of fraud in auto insurance // Izvestiya of Saratov University. Mathematics. Mechanics. Informatics. 4 (24), 619–628.

Забавин Д. В. 2009. Применение скоринговых систем в целях противодействия преступлениям в сфере страхования.

Банк России. 2025. Статистика. URL: https://cbr.ru/insurance/reporting_stat/ (дата обращения: 13.10.2025).

INFORMATION ABOUT AUTHOR / ИНФОРМАЦИЯ ОБ АВТОРЕ

KLIMENTOV Andrei R. – student.
E-mail: andreiklimentov361@gmail.com
КЛИМЕНТОВ Андрей Романович – студент.
E-mail: andreiklimentov361@gmail.com

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A COMPARATIVE ANALYSIS OF MACHINE LEARNING METHODS WITH THE APPLICATION OF THE KOLMOGOROV-GABOR POLYNOMIAL FOR FORECASTING SPORTS EVENT OUTCOMES

Daria Kovalevskaya[1,✉], Sergey Sventunkov[2]

[1] Peter the Great St. Petersburg Polytechnic University, St. Petersburg, Russia;
[2] Imperial College London, London, UK

✉ nesmelova2000@bk.ru

Abstract. The article presents a comparative analysis of the effectiveness of machine learning methods for predicting the results of football matches, with a focus on the application of the elementary image of the Kolmogorov-Gabor polynomial. The relevance of the study is due to the need to choose models that are balanced in accuracy, interpretability, and computational complexity in conditions of high stochasticity of sports data. The scientific novelty lies in the adaptation of the elementary image of the Kolmogorov-Gabor polynomial (KGp) for sports analytics tasks and its complex comparison with a wide range of algorithms, from classical regression to gradient boosting. Based on historical data, models have been built and analyzed: an elementary image of a polynomial, linear regression with regularization, a random forest, gradient boosting, and a neural network. The results were evaluated by metrics MAE and accuracy of predicting the outcome. A model based on an elementary image of a polynomial Kolmogorov-Gabor showed competitive accuracy comparable to more complex ensemble methods, while maintaining advantages in computational efficiency and the potential interpretability of the structure of nonlinear dependencies. It was concluded that it is advisable to use this approach as an effective tool for building hybrid forecasting systems in sports analytics.

Keywords: comparative analysis, prediction of results, football, elementary image of the Kolmogorov-Gabor polynomial, machine learning, sports analytics, gradient boosting, random forest, neural network, regression analysis

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СРАВНИТЕЛЬНЫЙ АНАЛИЗ МЕТОДОВ МАШИННОГО ОБУЧЕНИЯ С ПРИМЕНЕНИЕМ ПОЛИНОМА КОЛМОГОРОВА-ГАБОРА ДЛЯ ПРОГНОЗИРОВАНИЯ РЕЗУЛЬТАТОВ СПОРТИВНЫХ СОБЫТИЙ

Дарья Ковалевская[1,✉], Сергей Светуньков[2]

[1] Санкт-Петербургский политехнический университет Петра Великого, Санкт-Петербург, Россия;
[2] Имперский колледж Лондона, Лондон, Великобритания

✉ nesmelova2000@bk.ru

Аннотация. В статье представлен сравнительный анализ эффективности методов машинного обучения для прогнозирования результатов футбольных матчей, с фокусом на применении элементарного образа полинома Колмогорова-Габора. Актуальность исследования обусловлена необходимостью выбора сбалансированных по точности, интерпретируемости и вычислительной сложности моделей в условиях высокой стохастичности спортивных данных. Научная новизна заключается в адаптации элементарного образа полинома Колмогорова-Габора для задач спортивной аналитики и его комплексном сравнении с широким спектром алгоритмов — от классической регрессии до градиентного бустинга. На основе исторических данных построены и проанализированы модели: элементарный образ полинома, линейная регрессия, случайный лес, градиентный бустинг и нейронная сеть. Результаты оценивались по метрикам MAE и точности предсказания исхода. Модель на основе элементарного образа полинома Колмогорова-Габора (пКГ) показала конкурентную точность, сопоставимую с более сложными ансамблевыми методами, при этом сохранив преимущества в вычислительной эффективности и потенциальной интерпретируемости структуры нелинейных зависимостей. Сделан вывод о целесообразности использования данного подхода в качестве эффективного инструмента для построения гибридных прогнозных систем в спортивной аналитике.

Ключевые слова: сравнительный анализ, прогнозирование результатов, футбол, элементарный образ полинома Колмогорова-Габора, машинное обучение, спортивная аналитика, градиентный бустинг, случайный лес, нейронная сеть, регрессионный анализ

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Introduction

In the field of sports analytics, especially when predicting the outcomes of sports matches, analysts face the challenge of choosing a model that optimally combines accuracy, computational efficiency, and interpretability (Bunker R, Susnyak, 2022; Horvat, 2020). The high degree of stochasticity of this process, due to the influence of numerous factors, requires methods to be able to capture complex nonlinear dependencies in the data (Choi et al., 2023; Yeung et al., 2023). Traditional statistical approaches, such as linear or logistic regression, are often not flexible enough to describe such relationships (Andrianova et al.,2020; Afanasyev, 2020). In turn, modern machine learning methods, including ensemble algorithms (random forest, gradient boosting) and deep neural networks, demonstrate high approximation ability, but may have a number of disadvantages: high resource intensity, a tendency to overfitting on small samples and low interpretability, which limits their analytical value (Balasanyan, Gevorgyan, 2016; Avakyants, Urubkin, 2017; Vladimirova, 2004)

An elementary image of the Kolmogorov-Gabor polynomial can serve as a promising compromise (Svetunkov, 2024). This approach, while preserving its polynomial nature, significantly reduces the "curse of dimensionality" characteristic of a complete polynomial by a two-step transformation: linear convolution of input features followed by a nonlinear polynomial transformation of the result (Ivakhnenko, 1971; Zjavka, Snбљel, 2016). This makes it possible to effectively model nonlinear dependencies, while maintaining a relatively simple procedure for estimating coefficients. the least squares method. As a result, the model has increased interpretability and stability based on limited amounts of data typical for analyzing sports seasons compared to neural network architectures (Svetunkov, Chernyagin, 2024).

The relevance of the study is determined by the growing need for a methodology that allows not only to obtain accurate forecasts, but also to identify key factors affecting performance. Forecasting betting processes is of great practical importance for bookmakers and gamblers, as it allows them to assess the probability of an event outcome and make decisions about participating in betting (Isanberdin, 2022). At the same time, modeling betting processes is a difficult task, since such processes have nonlinear dynamics and non-stationarity. The scientific novelty consists in adapting and applying the elementary image of the Kolmogorov-Gabor polynomial to the task of predicting the results of football matches; in conducting a comparative analysis of the effectiveness of the elementary image of the KGp with basic (linear regression) and modern machine learning methods (gradient boosting, random forest, neural networks) on a single set of data and metrics; in evaluating the elementary the image of the KGp in terms of the balance between prediction accuracy, learning rate, and the potential for interpreting the resulting dependencies (Marateb et al., 2023; Yeung et al., 2023).

The aim of this article is to compare the accuracy and effectiveness of various machine learning methods, including the elementary image of the Kolmogorov-Gabor polynomial, for predicting quantitative (total number of goals in a match) (Belov, Chistyakova, 2008). To achieve the goal, the following tasks are being solved: a) collection and preprocessing of a set of historical data; b) implementation of a model based on an elementary image of the KGp and training and validation of alternative models; c) comparative analysis of results based on a set of metrics (MAE, RMSE, accuracy) and visualizations.

Materials and Methods

Historical data from Zenit football club matches from open sources was used to build and compare models. The target variable y was the number of goals scored by the team in a particular match (an integer value from 0 to 8). Eight indicators characterizing the match and the opponent were used as independent variables (signs):

x_1: match status (1 – home, 0 – away);

x_2: the average number of goals conceded by the opponent at home and away during the season;

x_3: the opponent's position in in the standings;

x_4: the number of goals scored by the opponent in previous matches;

x_5: the percentage of possession of the opposing team;

x_6: the average number of shots allowed by the opponent on his own goal per match;

x_7: the percentage of matches in which the opponent did not concede goals (percentage of "dry" matches);

x_8: the average number of goals scored by the opponent in the matches of the season;

x_9: the average number of expected goals that the opponent can concede in the match (xGA).

All features were standardized before being used in polynomial and linear models:

$$x_i' = \frac{x_i - \mu_i}{\sigma_i}$$

Where μ_i and σ_i – the mean and standard deviation of the sample.

As part of a comparative analysis of machine learning methods for predicting sports events, five different machine learning algorithms were implemented and evaluated: an elementary image of a polynomial, linear regression with regularization, a random forest, gradient boosting, and a neural network.

The Kolmogorov-Gabor polynomial (KGp) is a functional series designed to approximate complex nonlinear dependencies between multiple input variable $x_1, x_2, ..., x_m$ and the output variable y. It has the following form for m=3 (number of factors) (Svetunkov, 2024):

$$y = a_0 + \sum_{i=1}^{3} a_i x_i + \sum_{i=1}^{3}\sum_{j=i}^{3} a_{ij} x_i x_j + \sum_{i=1}^{3}\sum_{j=i}^{3}\sum_{k=j}^{3} a_{ijk} x_i x_j x_k + ...$$

The main disadvantage of the full KGp is the exponential growth in the number of terms with an increase in the number of factors m, which leads to the problem of the "curse of dimensionality" and increases the risk of overfitting. To overcome these limitations, the paper uses an elementary image of the Kolmogorov-Gabor polynomial, a simplified two-stage model:

1. Linear convolution signs:

$\hat{y}' = b_0 + b_1 x_1 + b_2 x_2 + ... + b_m x_m$

2. Polynomial convolution transform:

$\hat{y} = c_0 + c_1 \hat{y}' + c_2 (\hat{y}')^2 + ... + c_k (\hat{y}')^k$

where k – the degree of the polynomial (usually k $\leq$ 4).

The coefficients are b_i and c_i estimated using the ordinary least squares (OLS) method. This approach retains the ability to approximate nonlinear dependencies with a significantly smaller number of estimated parameters.

The practical implementation of the elementary image of the KGp in the work was carried out through an equivalent construction based on second-order polynomial features:

– the original features were scaled using StandardScaler;

– the transformation into a second-order polynomial space (including all squares and pairwise products of features) was performed;

– ridge regression with L2 regularization was used to estimate the coefficients (Izonin et al., 2024; Selvaraj et al., 2016):

$$\hat{y} = X_{poly}\beta \text{, where } \beta = \arg\min_{\beta} \left\| y - X_{poly}\beta \right\|^2 + \alpha \left\| \beta \right\|^2$$

where X_{poly} is the matrix of extended polynomial features, and α = 1.0 is the regularization coefficient.

The final predictions were rounded to integers and limited to the range [0, 8] corresponding to the realistic number of goals in a football match.

To conduct a comparative analysis, in addition to the elementary image of the KGp, the following algorithms were implemented:

1. Linear regression is a classic statistical method which serves as a baseline for estimating the minimum achievable accuracy using linear methods.

2. Random Forest is an ensemble method based on bagging, which builds a set of decision trees on various subsamples of data and features, then aggregates them predictions by averaging. The algorithm effectively captures nonlinear dependencies and interactions between features,

and is resistant to overfitting and outliers.

3. Gradient Boosting is a modern ensemble method that consistently builds decision trees, each of which learns from the mistakes of the previous ones. Gradient boosting refers to state-of-the-art approaches for tabular data and often shows the best results in regression tasks. The implementation was used in the work GradientBoostingRegressor with 100 trees, a maximum depth of 3 and a learning rate of 0.1.

4. Fully connected Neural Network (Neural Network) is a deep learning model with one hidden layer of 128 neurons with a ReLU activation function. The training was conducted over 30 epochs using the Adam optimizer and the MSE loss function. Neural networks have a high approximation capability (the universal approximation theorem), but require more computational resources and are more difficult to interpret compared to other methods (Svetunkov, 2024).

For the assessment and comparison of models the following metrics were used:

1. Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, n is the number of observations. MAE measures the average magnitude of the forecast error in natural units (goals).

2. Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

RMSE is more sensitive to large forecast errors, which is important when assessing risks in forecasts.

3. Accuracy:

$$Accuracy = \frac{Number\ of\ exact\ matches}{Total\ number\ of\ predictions} * 100\%$$

4. Accuracy ± 1 goal is the percentage of matches in which the discrepancy between the forecast and the fact did not exceed one goal. This metric is important for assessing the practical applicability of models in conditions of high stochasticity of football matches, where accurate prediction of a specific score It is an extremely difficult task.

Results and Discussions

As part of the study, five machine learning models were built and tested to predict the number of goals scored by Zenit Football club in the last 10 matches of the 2022-2023 season. To assess the quality of forecasts, the metrics of average absolute error (MAE), RMS error (RMSE), the proportion of exact matches and the proportion of matches with a deviation of no more than one goal were used. The results of the comparative analysis are presented in Table 1.

Table 1. Comparison of forecast accuracy of different models.

Model	MAE	RMSE	Accuracy	Accuracy ± 1 goal
Elementary image of the KGp	1.5	1.97	30%	50%
Linear Regression	1.5	1.92	30%	50%
Random Forest	1.2	1.61	20%	80%
Gradient boosting	1.3	1.76	30%	60%
Neural network model	1.1	1.3	20%	70%

In a comparative analysis of five Zenit performance forecasting models based on the metrics MAE, RMSE, accuracy and accuracy ± 1 goal, the neural network showed the best result for MAE (1.1) and RMSE (1.30), which indicates the minimum average deviation of forecasts. However, in terms of practical applicability (±1 goal), a random forest leads with a score of 80%, while the neural network demonstrates 70%, and the elementary image of the Kolmogorov-Gabor polynomial and linear regression are 50% each. At the same time, according to the accuracy of the exact matches of the KGp, the linear regression and gradient boosting showed a maximum of 30%, while more complex models showed 20%. Thus, for tasks where the minimum average error is critical, a neural network is optimal; for the maximum practical usefulness of forecasting, a random forest; and for analytical tasks requiring interpretability of the contribution of features, the elementary image KGp, which, without yielding in accuracy, ensures the transparency of the model by analyzing the coefficients of the polynomial.

Figure 1 shows the predicted values of the model based on the elementary image of the Kolmogorov–Gabor polynomial compared to the actual results. Figures 2,3,4,5 illustrate the results for the linear regression, random forest, gradient boosting and neural network models, respectively. A summary comparison of the three models is presented in Figure 6.

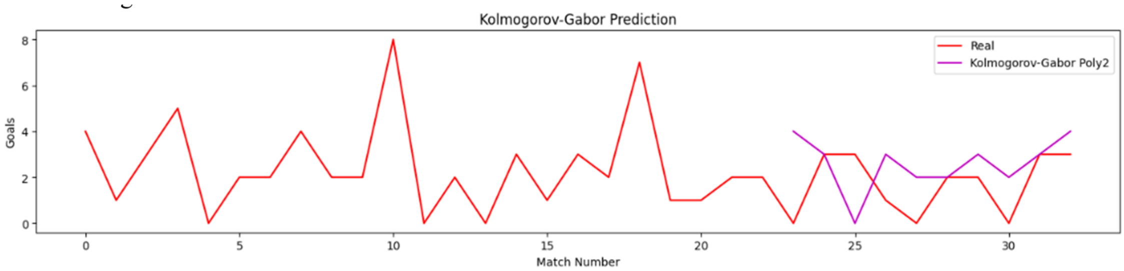

Fig. 1. Graph of the forecast of the number of goals scored by the Zenit team for 10 matches using a model based on the elementary image of the Kolmogorov–Gabor polynomial.

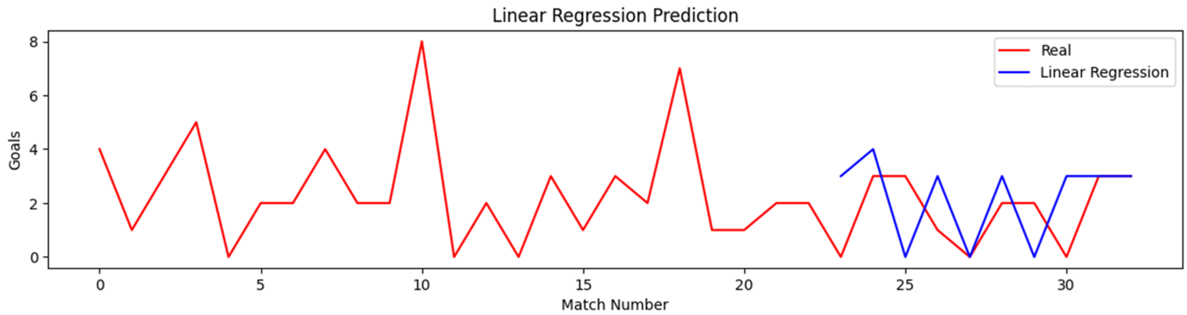

Fig. 2. Graph of the forecast of the number of goals scored by the Zenit team for 10 matches using a model based on the linear regression.

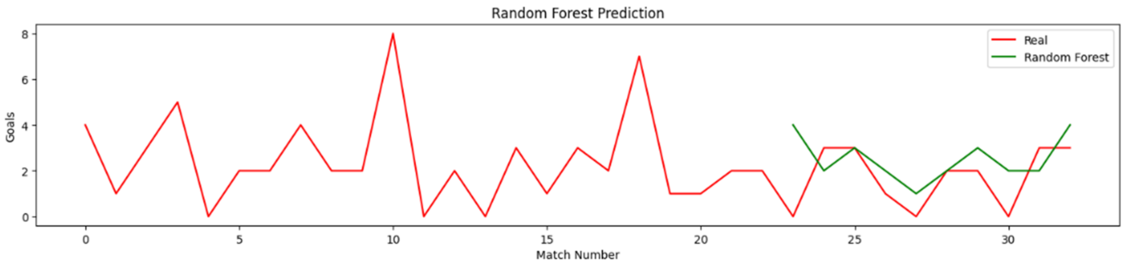

Fig. 3. Graph of the forecast of the number of goals scored by the Zenit team for 10 matches using the random forest model.

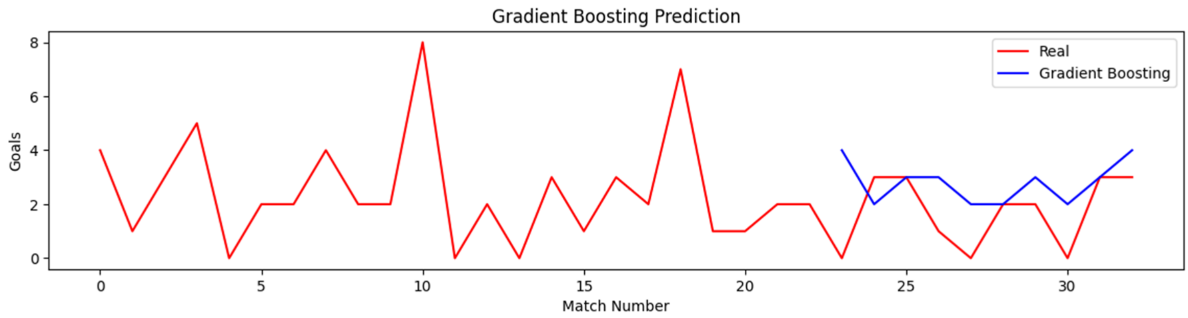

Fig. 4. Graph of the forecast of the number of goals scored by the Zenit team for 10 matches using a model based on the gradient boosting.

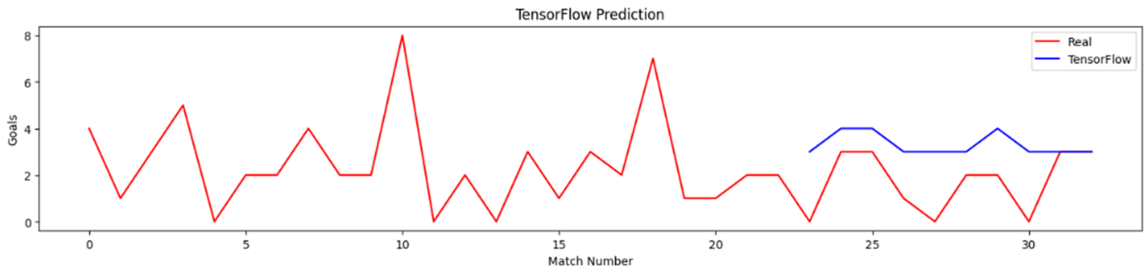

Fig. 5. Graph of the forecast of the number of goals scored by the Zenit team for 10 matches based on a neural network model.

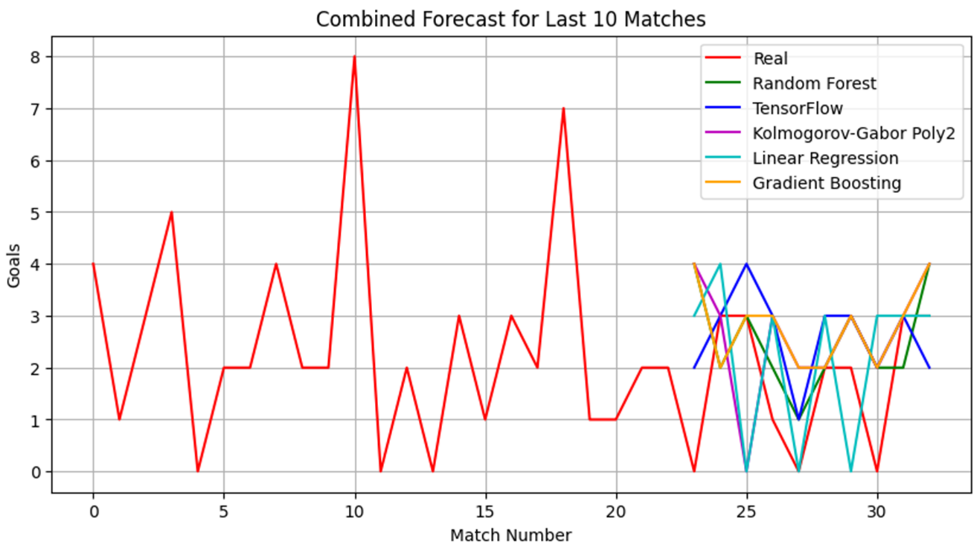

Fig. 6. Comparison of model forecasts with actual values of the number of goals scored by the Zenit team.

To demonstrate the key advantage of the model - its interpretability - an analysis of the most significant features in the polynomial model was carried out. Since the elementary image of the Kolmogorov-Gabor polynomial is implemented through second-order polynomial features, we can analyze the coefficients of the resulting model. Figure 7 shows the top 10 most significant terms of the polynomial.

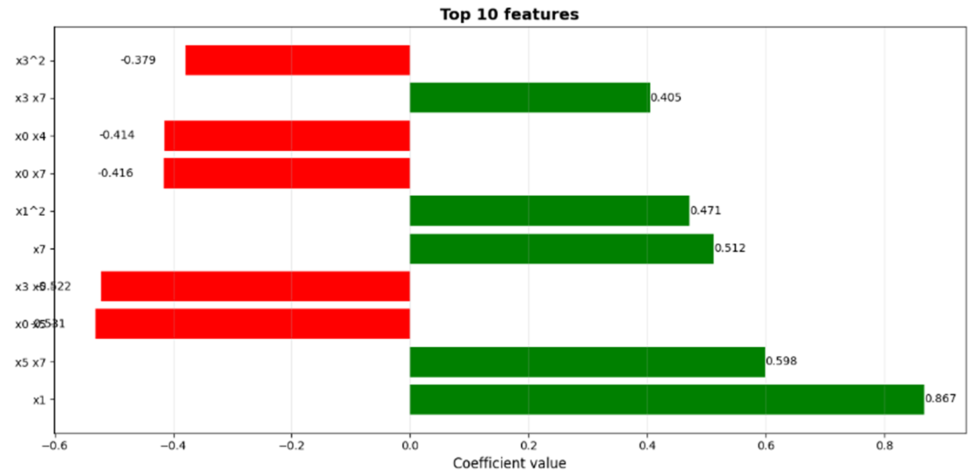

Fig. 7. Top 10 most significant terms of the polynomial.

The analysis of the significance of the coefficients of the polynomial model revealed the key performance factors of FC Zenit. The most significant individual factor turned out to be the status of the match: playing at home significantly increases the likelihood of more goals scored (Bussgang et al., 1974). The second most powerful limiting factor was the defensive reliability of the opponent, measured by the percentage of "dry" matches. At the same time, the greatest complex threat to Zenit's attack is created by teams combining high ball possession with organized defense - their interaction in the model showed the maximum negative effect after the home factor. Non-linear effects, such as the square of home status, and interactions, such as the opponent's position with his defensive discipline, also have a significant impact. These results emphasize that for an accurate forecast, it is necessary to take into account not only the individual indicators of the opponent, but also their impact depending on the conditions of the match (Enikeeva, 1992).

Conclusion

As part of the research, the main goal was successfully achieved - a comparative analysis of the accuracy and effectiveness of various machine learning methods for the task of quantifying the performance of football matches was carried out. Special attention was paid to assessing the prospects of using the elementary image of the Kolmogorov-Gabor polynomial in the context of sports analytics (Luparev, Svetunkov, 2025). To achieve this goal, all tasks have been consistently solved: the collection and preprocessing of a set of historical match data has been carried out; and a forecasting model based on the elementary image of the KGp has been implemented; in parallel, they have been trained alternative models: linear regression, random forest, gradient boosting, neural networks); a comparative analysis of their work was carried out based on a comprehensive set of metrics (MAE, RMSE, accuracy, accuracy ± 1 goal) using visualization methods. The results obtained allow us to state that the model based on the elementary image of the Kolmogorov-Gabor polynomial has demonstrated a quite competitive level. accuracy. The indicator of 30% accurate matches of the actual and predicted values of the number of heads is not inferior to the results shown by such modern and powerful methods as gradient boosting, and even surpasses the random forest and neural network model in this parameter. This is a significant result, given the relative simplicity and computational efficiency of the polynomial model compared to more complex algorithms (Enikeeva, 1992; Vereshchagin, 2013; Chernyagin, 2024)

At the same time, as expected, the key advantage of the complementary image of the KGp over the alternatives remains its full interpretability and explainability. Unlike "black box" models (neural networks, ensembles of trees), the structure of the polynomial allows not only to make a forecast, but also to conduct a deep analytical analysis of the factors that determine it. The researcher gets the opportunity to quantify the contribution of each initial feature (match status, opponent statistics, etc.), as well as analyze the strength and nature of nonlinear interactions between them. This It transforms the model from a simple forecasting tool into a powerful analytical research tool capable of generating meaningful hypotheses about the nature of athletic performance. Of course, by metrics such as the average absolute error (MAE=1.5) and the standard deviation (RMSE=1.97), the polynomial model is inferior to the best of the considered algorithms. However, this gap in accuracy can be considered an acceptable price to pay for the acquired quality - transparency and controllability of the forecasting process. In applied conditions, especially in the expert environment of coaches, analysts, and managers of sports clubs, the ability to understand and argue the reasons for a forecast is often valued no less, and sometimes more, than its extreme accuracy.

Thus, the results confirm the main hypothesis of the study: the elementary image of the Kolmogorov-Gabor polynomial represents an effective methodological compromise. It offers a balance between predictive power sufficient for practical use and a degree of explainability. This makes it a valuable tool not only in the arsenal. a data science specialist who solves the problem of forecasting, but also in the hands of a sports analyst who strives for an in-depth, causal understanding of the factors influencing the success of a team. The prospects for further development of the method are seen in the study of higher-order polynomials, the combination of elementary KGp with other algorithms within the framework of ensemble approaches, as well as in the adaptation of the methodology to other classes of predictive tasks in sports analytics (Iliyasu et al., 2023).

REFERENCES

Avakyants A.V., Urubkin M.Y. 2017. Forecasting methods. Innovative Science 2-1. URL: https://cyberleninka.ru/article/n/metody-prognozirovaniya (date of request: 12.01.2026).

Andrianova E.G., Golovin S.A., Zykov S.V., Lesko S.A., Chukalina E.R. 2020. An overview of modern models and methods for analyzing time series of process dynamics in social, economic and sociotechnical systems. Russian Technical Journal 8 (4), 7-45. doi:10.32362/2500-316X-2020-8-4-7-45.

Afanasyev V.N. 2020. Time series analysis and Forecasting, 286.

Balasanyan. S.Sh , Gevorgyan E.M. 2016. Comparative analysis of regression methods and group consideration of arguments in the modeling of mineral processing processes. Georesource Engineering 327 (4), 23-34.

Belov V.V., Chistyakova V.I. 2008. Modeling and forecasting of business processes using algorithms for self-organization of formal descriptions. Business Informatics 4 (06), 37-45.

Bunker R., Susnyak T. 2022. Application of machine learning methods for predicting match results in team sports: An overview. Journal of Artificial Intelligence Research, 73, 1285-1322.

Bussgang J.J., Ehrman L., Graham J.W. 1974. Analysis of nonlinear systems with multiple inputs. Proceedings of IEEE 62(8), 1088-1119. doi:10.1109/PROC.1974.9572.

Vereshchagin N.K., Uspensky V.A., Shen A. 2013. Kolmogorov complexity and algorithmic randomness, 575.

Vladimirova L.P. 2004. Forecasting and planning in market conditions, 298.

Enikeeva V.D. 1992. Application of Kolmogorov-Gabor polynomials to predict the height of the lower cloud boundary. Meteorological forecasts. Volume Issue 114, 82-86.

Choi B.S., Fu L., Chua S. 2023. Predicting the results of football matches using machine learning methods. MENDEL 29 (2), 229-236. doi:10.13164/mendel.2023.2.229.

Horvat T. 2020. Using machine learning to predict athletic performance: an overview. Interdisciplinary Wiley Reviews: Data Mining and Knowledge Disclosure 10 (1). doi: 10.1002/widm.1380.

Iliyasu A.M., Bagaudinovna D.K., Salama A.S. 2023. A methodology for analyzing and predicting the volume fraction of a two-phase flow using swarm optimization of particles and the group method of a neural network of data processing. Mathematics 11 (4), 916. doi:10.3390 / math11040916.

Isanberdin A.A. 2022. Econometric methods of forecasting demand. Education: professional debut. Collection of materials of the VIII International Scientific Conference
and Practical Conference, 193-196.

Ivakhnenko A.G. 1971. The polynomial theory of complex systems. IEEE Proceedings on Systems, Humans, and Cybernetics SMC-1(4), 364-378.

Izonin I., Tkachenko R., Yemets K., Gavrilyuk M. 2024. An interpreted ensemble structure with a non-iterative learning algorithm to improve prediction accuracy when analyzing medical data. Scientific Reports 14, 12947. doi:10.1038/s41598-024-61776- G.

Luparev K., Svetunkov S. 2025. The possibility of building a universal nonlinear autoregression. The Encyclopedia 4 (1 (12)), 4-12. doi:10.57809/2025.4.1.12.1.

Marateb H., Noruzirad M., Tavakolyan K. 2023. Predicting the length of hospital stay due to COVID-19 using Kolmogorov-Gabor polynomials: charting the future of medical care. Information 14 (11), 590. doi:10.3390/info14110590.

Selvaraj P., Vekman G.R., Snow A.P. 2016. Group method of data processing: how effective is it? ALLDATA 2016: The Second International Conference on Big Data, Small Data, Connected Data and Open Data: Proceedings.

Svetunkov S.G. 2024. An elementary image of the Kolmogorov-Gabor polynomial in economic modeling. The Encyclopedia 3 (2 (9)), 4-21. doi:10.57809/2024.3.2.9.1.

Svetunkov S.G. 2024. Polynomial networks instead of neural networks. The Encyclopedia 3 (3 (10)), 57-71. doi:10.57809/2024.3.3.10.6.

Svetunkov S.G., Chernyagin A.S. 2024. Neural network and Kolmogorov-Gabor polynomial in modeling complex economic processes. Success in Modern Economics 4, 153-158. doi:10.58224/2500-3747- 2024-4-153-158 .

Chernyagin A.S. 2024. Adaptive machine learning model based on the Kolmogorov-Gabor polynomial. DOI: 10.18720/SPBPU/3/2024/ vr/VR24-3989.

Yeung C.C.K., Bunker R., Fujii K. 2023. A framework of interpretable match results prediction in football with FIFA ratings and team formation. PLoS ONE 18 (4). doi:10.1371/journal.pone.0284318.

Zjavka L., Snasel V. 2016. Short-term power load forecasting with ordinary differential equation substitutions of polynomial networks. Electric Power Systems Research 137, 113-123. doi:10.1016/j.epsr.2016.04.011.

СПИСОК ИСТОЧНИКОВ

Авакьянц А.В., Урубкин М.Ю. 2017. Методы прогнозирования. Инновационная наука 2-1. URL: https://cyberleninka.ru/article/n/metody-prognozirovaniya (дата обращения: 12.01.2026).

Андрианова Е.Г., Головин С.А., Зыков С.В., Лесько С.А., Чукалина Е.Р. 2020. Обзор современных моделей и методов анализа временных рядов динамики процессов в социальных, экономических и социотехнических системах. Российский технологический журнал 8 (4), 7-45. doi:10.32362/2500-316X-2020-8-4-7-45.

Афанасьев В.Н. 2020. Анализ временных рядов и прогнозирование, 286.

Balasanyan S.Sh., Gevorgyan E.M. 2016. Comparative analysis of regression methods and group accounting of arguments in modeling mineral processing processes. Georesources Engineering 327 (4), 23-34.

Белов В.В., Чистякова В.И. 2008. Моделирование и прогнозирование бизнес-процессов с помощью алгоритмов самоорганизации формальных описаний. Бизнес-информатика 4 (06), 37-45.

Bunker R., Susnjak T. 2022. The Application of Machine Learning Techniques for Predicting Match Results in Team Sport: A Review. Journal of Artificial Intelligence Research 73, 1285-1322.

Bussgang J.J., Ehrman L., Graham J.W. 1974. Analysis of nonlinear systems with multiple inputs. IEEE Proceedings 62 (8), 1088-1119. doi:10.1109/PROC.1974.9572.

Верещагин Н.К., Успенский В.А., Шень А. 2013. Колмогоровская сложность и алгоритмическая случайность, 575.

Владимирова Л.П. 2004. Прогнозирование и планирование в условиях рынка, 298.

Еникеева В.Д. 1992. Применение полиномов Колмогорова-Габора для прогноза высоты нижней границы облачности. Метеорологические прогнозы. Том Выпуск 114, 82-86.

Choi B.S., Foo L., Chua S. 2023. Predicting Football Match Outcomes with Machine Learning Approaches. MENDEL 29 (2), 229-236. doi:10.13164/mendel.2023.2.229.

Horvat T. 2020. The use of machine learning in sport outcome prediction: A review. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 10 (1). doi:10.1002/widm.1380.

Iliyasu A.M., Bagaudinovna D.K., Salama A.S. 2023. A Methodology for Analysis and Prediction of Volume Fraction of Two-Phase Flow Using Particle Swarm Optimization and Group Method of Data Handling Neural Network. Mathematics 11 (4), 916. doi:10.3390/math11040916.

Исанбердин А.А. 2022. Эконометрические методы прогнозирования спроса. Образование: профессиональный дебют. Сборник материалов VIII Международной студенческой научно-практической конференции, 193-196.

Ivakhnenko A.G. 1971. Polynomial Theory of Complex Systems. IEEE Transactions on Systems, Man, and Cybernetics SMC-1 (4), 364-378.

Izonin I., Tkachenko R., Yemets K., Havryliuk M. 2024. An interpretable ensemble structure with a non-iterative training algorithm to improve the predictive accuracy of healthcare data analysis. Scientific Reports 14, 12947. doi:10.1038/s41598-024-61776-y.

Лупарев К., Светуньков С. 2025. Возможность построения универсальной нелинейной авторегрессии. Техноэкономика 4 (1 (12)), 4-12. doi:10.57809/2025.4.1.12.1.

Marateb H., Norouzirad M., Tavakolian K. 2023. Predicting COVID-19 Hospital Stays with Kolmogorov-Gabor Polynomials: Charting the Future of Care. Information 14 (11), 590. doi:10.3390/info14110590.

Selvaraj P., Weckman G.R., Snow A.P. 2016. Group Method of Data Handling: How does it measure up? ALLDATA 2016: The Second International Conference on Big Data, Small Data, Linked Data and Open Data: proceedings.

Светуньков С.Г. 2024. Элементарный образ полинома Колмогорова - Габора в моделировании экономики. Техноэкономика 3 (2 (9)), 4-21. doi:10.57809/2024.3.2.9.1.

Светуньков С.Г. 2024. Полиномиальные сети вместо нейронных сетей. Техноэкономика 3 (3 (10)), 57-71. doi:10.57809/2024.3.3.10.6.

Светуньков С.Г., Чернягин А.С. 2024. Нейронная сеть и полином Колмогорова-Габора в моделировании сложных экономических процессов. Modern Economy Success 4, 153-158. doi:10.58224/2500-3747- 2024-4-153-158.

Чернягин А.С. 2024. Адаптивная модель машинного обучения на основе полинома Колмогорова-Габора. DOI: 10.18720/SPBPU/3/2024/vr/vr24-3989.

Yeung C.C.K., Bunker R., Fujii K. 2023. A framework of interpretable match results prediction in football with FIFA ratings and team formation. PLoS ONE 18 (4). doi:10.1371/journal.pone.0284318.

Zjavka L., Snasel V. 2016. Short-term power load forecasting with ordinary differential equation substitutions of polynomial networks. Electric Power Systems Research 137, 113-123. doi:10.1016/j.epsr.2016.04.011.

INFORMATION ABOUT AUTHOR / ИНФОРМАЦИЯ ОБ АВТОРЕ

KOVALEVSKAYA Daria N. – student.
E-mail: nesmelova2000@bk.ru
КОВАЛЕВСКАЯ Дарья Николаевна – студент.
E-mail: nesmelova2000@bk.ru

SVETUNKOV Sergey G. – Professor, Doctor of Economic Sciences
E-mail: sergey@svetunkov.ru
СВЕТУНЬКОВ Сергей Геннадьевич – профессор, д.э.н.
E-mail: sergey@svetunkov.ru
ORCID: https://orcid.org/0000-0001-6251-7644

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INTERRELATION OF BUSINESS PROCESS MATURITY AND SPIRAL DYNAMICS STAGES IN ENTERPRISES

Tatyana Shmygol ✉

Peter the Great St. Petersburg Polytechnic University, St. Petersburg, Russia

✉ tanya.shmygol@mail.ru

Abstract. The article explores the correlation between business process maturity levels and organizational development stages, as defined by the Spiral Dynamics framework. The research object is technology-intensive enterprises undergoing scaling and digital transformation. The methodological approach integrates maturity assessment tools, including process audits, structured interviews, and integrated maturity process index (MPI) calculation, with Spiral Dynamics diagnostics based on adapted questionnaires, hierarchy index analysis, and critical incident interviews. Results demonstrate a statistically significant correlation between process maturity and organizational value stages. Case analysis revealed that IT startups tended to shift from Orange to Green stages, while GMP-certified plants maintained Blue dominance despite advanced process maturity. The findings highlight cultural alignment as a decisive factor for successful digital transformation. Practical recommendations are proposed for phased standardization in early-stage organizations, cultural adaptation strategies in regulated enterprises, and conflict-resolution mechanisms in hybrid environments.

Keywords: business process maturity, spiral dynamics, organizational development, cultural alignment, digital transformation, process management, IT startups, regulated industries, innovation hubs, organizational culture

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СООТНОШЕНИЕ УРОВНЕЙ ЗРЕЛОСТИ БИЗНЕС-ПРОЦЕССОВ И СТАДИЙ РАЗВИТИЯ ПО СПИРАЛЬНОЙ ДИНАМИКЕ В ПРЕДПРИЯТИЯХ

Татьяна Шмыголь ✉

Санкт-Петербургский политехнический университет Петра Великого,
Санкт-Петербург, Россия

✉ tanya.shmygol@mail.ru

Аннотация. Статья посвящена анализу взаимосвязи между уровнем зрелости бизнес-процессов и стадиями организационного развития, определяемыми в рамках модели спиральной динамики. Объектом исследования выступают предприятия высокотехнологичных отраслей, находящиеся в стадии масштабирования и цифровой трансформации. Методологический подход включает применение инструментов оценки зрелости, в том числе аудита процессов, структурированных интервью и расчёта интегрального индекса зрелости процессов (MPI), в сочетании с диагностикой по спиральной динамике на основе адаптированных опросников, анализа индекса иерархичности и метода критических инцидентов. Результаты показали статистически значимую корреляцию между уровнем зрелости процессов и стадиями ценностного развития организаций. Кейс-анализ выявил, что IT-стартапы имеют тенденцию перехода от стадии «Оранжевой» к «Зелёной», тогда как предприятия с сертификацией сохраняют доминирование «Синей» стадии, несмотря на высокий уровень зрелости процессов. Полученные результаты подчеркивают, что культурное согласование является ключевым фактором успешной цифровой трансформации. В практическом плане предложены рекомендации по поэтапной стандартизации для организаций раннего развития, стратегиям культурной адаптации для регулируемых отраслей, а также механизмам разрешения конфликтов в гибридных организационных средах.

Ключевые слова: зрелость бизнес-процессов, спиральная динамика, организационное развитие, культурное согласование, цифровая трансформация, управление процессами, IT-стартапы, регулируемые отрасли, инновационные хабы, организационная культура

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Introduction

The object of this study is organizations operating in technology-intensive industries – primarily IT scale-ups, pharmaceutical plants under GMP regulation, and corporate innovation hubs – where business process formalization and cultural transformation occur simultaneously. These companies face the dual challenge of achieving process standardization while adapting their organizational culture to conditions of rapid growth and digitalization. The selected organizations represent sectors where both the requirements for regulatory compliance and the need for continuous innovation are especially acute, making them appropriate cases for examining the interplay between process maturity and cultural development.

The relevance of the study arises from the fact that most digital transformation initiatives fail to achieve their intended outcomes. According to Gartner (2023), nearly 70% of such programs underperform, while McKinsey (2022) identifies cultural resistance as the primary barrier to sustainable transformation. Even organizations that achieve high maturity levels in terms of business process management (e.g., MPI > 4.0) often fail to realize the expected benefits because of cultural inertia. Conversely, organizations with adaptive cultural systems sometimes embrace innovation but lack the process discipline needed for scaling. These findings highlight that process formalization and cultural adaptability represent complementary but not interchangeable drivers of organizational success.

A significant body of literature exists on Business Process Maturity Models (BPMM). Frameworks such as CMMI, ISO 330xx, PEMM, OPM3, and more recent approaches describe progressive stages of maturity from ad-hoc to optimized processes (Van Looy, 2021). Studies emphasize their role in improving quality, predictability, and efficiency (Flechsig et al., 2022). BPMM applications have expanded beyond IT and software engineering to include healthcare, manufacturing, logistics, and other domains, confirming their relevance as universal tools for organizational development. At the same time, critical reviews note that maturity assessments often overlook soft factors such as leadership styles, communication practices, and organizational values, which are essential for sustainable change.

Parallel to this, Spiral Dynamics identifies successive developmental tiers within collective value systems. These include a tier centered on structure, discipline, and adherence to established authority (traditionally associated with a “Blue” coding), followed by a tier oriented toward strategic innovation, individual achievement, and competitive market dynamics (often coded as “Orange”). The progression further extends to a tier that prioritizes communal well-being, collaborative networks, and empathetic, consensual decision-making frameworks (typically referenced with a “Green” code). These distinct value configurations become materially embedded in an organization's structural design and its prevailing operational and managerial methodologies (Martinek-Jaguszewska et al., 2022). Recent empirical studies demonstrate the applicability of Spiral Dynamics to diagnosing organizational readiness for transformation, especially in the context of cross-cultural and knowledge-intensive environments (Schunter, 2025).

Nevertheless, the intersection of these two perspectives remains underexplored. Existing studies either focus on process formalization without considering cultural dynamics or analyze cultural evolution independently of process maturity. Research linking the two – for example, examining how maturity levels correlate with specific value stages – is scarce. While maturity models provide metrics for assessing procedural development, and Spiral Dynamics highlights cultural readiness, there is limited work that empirically integrates these approaches to capture their combined effect on transformation outcomes.

This work builds on the contributions of Van Looy (2021) in comparative analysis of maturity models, Flechsig et al. (2022) in studying digital transformation maturity, and Olsen et al. (2023) in exploring cultural barriers to organizational change. It also draws on recent studies that adapt Spiral Dynamics to organizational contexts, synthesizing insights from both streams of literature. By integrating these perspectives, the study addresses the identified gap and provides a framework for analyzing dual dependencies of process maturity and cultural stage.

The aim of the study is to analyze the correlation between business process maturity levels and organizational development stages as defined by Spiral Dynamics. To achieve this aim, the following objectives are set:

1. To identify representative organizational contexts where both process maturity and cultural dynamics are observable.

2. To design a methodology integrating maturity assessment (MPI) and Spiral Dynamics

diagnostics.

3. To validate correlations empirically through case studies in IT, pharmaceutical, and innovation hub environments.

4. To interpret the implications of mismatches between process maturity and cultural stages for managers and policymakers.

Materials and Methods

The study was designed as a multiple case analysis of organizations operating in technology-intensive industries. This approach was selected because it enables comparative insights across different contexts while preserving the depth of within-case investigation. The analysis covered three categories of organizations, representing distinct regulatory and operational environments:

1. IT scale-ups (50–500 employees), characterized by rapid growth, implementation of Agile/DevOps practices, and transitions from entrepreneurial to more formalized structures. These companies were chosen because they frequently face challenges of codifying informal knowledge and scaling collaborative practices into standardized processes.

2. Pharmaceutical and aviation manufacturers, operating under strict GMP and IATF compliance. These firms are subject to high requirements for process documentation, risk management, and external audits. They represent a context where maturity models are often applied, but cultural adaptability is limited by formal regulations.

3. Corporate innovation hubs, functioning as adaptive units embedded in larger bureaucratic organizations. These entities often display divergence between their own progressive culture and the conservative environment of parent companies, making them valuable for exploring conflicts between maturity and cultural alignment.

Organizations were selected according to two inclusion criteria: (1) the availability of reliable and verifiable data on process maturity, and (2) evidence of observable cultural patterns that could be consistently mapped to Spiral Dynamics stages (Szelagowski et al., 2024). Cases that lacked transparency or sufficient access for data triangulation were excluded.

Data were collected using a triangulation approach, which combined artifacts, structured interviews, and direct observation. This design was intended to minimize bias and ensure robust validity.

Artifact audits included the examination of documented process outputs:

1. IT companies: GitHub commit frequency, unit test coverage (>70% threshold), and CI/CD build success rate (>85%) were used as indicators of technical process discipline.

2. Manufacturing companies: PFMEA maps, MES downtime logs (>300 events per quarter), and SCADA deviations provided objective metrics of operational stability.

3. Pharmaceutical companies: GMP deviation reports and CAPA closure times reflected compliance and corrective practices.

Structured interviews were conducted with middle managers, team leaders, and compliance officers. A standardized protocol was developed using OPM3 and ISO/IEC 330xx as reference frameworks (Olsen et al., 2023). Sample questions included:

1. “What criteria are used to trigger process redesign?”

2. “Which KPIs are monitored to ensure process stability?”

3. “How are deviations escalated and resolved?”

Interviews were audio-recorded, transcribed verbatim, and analyzed through grounded theory coding. Codes were validated by two independent researchers to increase inter-coder reliability.

Direct observation consisted of shadowing 3–5 critical process cycles within each organization. Observers mapped process execution against ISO/IEC 33020 benchmarks, recording deviations and corrective actions. Field notes were later compared with formal documentation to validate consistency (Moedt et al., 2024).

Business process maturity was assessed using the Maturity Process Index (MPI), defined as:

$$MPI = \frac{\sum (W_i * L_i)}{N}$$

where W_i is the weight assigned to process area i (e.g., R&D = 0.4, Quality Control = 0.3, Supply Chain = 0.3), L_i is the maturity level (1–5), and N is the number of processes evaluated (Shcheleyko and Kreshtinkova, 2024).

This weighted composite score allowed for differentiation between sectors where certain processes (e.g., R&D in IT, Quality Control in Pharma) are disproportionately critical to performance.

Organizational culture was assessed using the Spiral Dynamics Index (SD_Index), a composite measure integrating three diagnostic instruments (Feld, 2022):

1. GVST–4 questionnaire, adapted for organizational contexts. Reliability testing yielded Cronbach's α > 0.80.

2. Hierarchy Index (HI), derived from linguistic analysis of internal documents. Ratios of directive vs. cooperative verbs were calculated, with values such as Pharma HI = 2.5 and IT HI = 1.1.

3. Critical Incident Technique (CIT), applied through interviews focusing on company responses to crises such as regulatory audits, product recalls, and scaling bottlenecks.

The composite index was calculated as:

$$SD\_Index = 0,4 * GV\ ST + 0,3 * HI + 0,3 * CIT$$

This weighting scheme was chosen to balance psychometric reliability (GVST) with behavioral and documentary evidence (HI and CIT).

To ensure reproducibility and robustness of results:

1. Reliability. All instruments were tested using Cronbach's α, with thresholds above 0.70 considered acceptable. Inter-coder reliability in qualitative coding exceeded 85% (Baroiu, 2022).

2. Triangulation. Artifact audits, interview data, and observational data were cross-validated. Discrepancies between sources were explicitly documented and analyzed.

3. Statistical testing. Spearman's rank correlation was used to test monotonic relationships, while linear regression models were applied to evaluate predictive validity of MPI for SD_Index (Ilyin, 2022).

4. Ethical considerations. All participants were informed about the purpose of the study, and sensitive data (e.g., audit results, incident reports) were anonymized before analysis.

Results and Discussion

The quantitative analysis revealed a statistically significant positive correlation between process maturity and cultural development stages. The linear regression demonstrated $R^2 = 0,61$, with $p < 0,05$, indicating that process maturity is a reliable predictor of organizational culture alignment (Aubouin-Bonnaventure et al., 2023). This result suggests that improvements in the formalization of processes are generally accompanied by movement to higher value stages within Spiral Dynamics.

Figure 1 shows the regression relationship between MPI and SD_Index, confirming the presence of a linear dependency. However, not all organizations followed the trend equally. Outliers, such as pharmaceutical plants with MPI above 4.0 but stagnating SD_Index values, indicate a mismatch between formalized processes and conservative cultural environments (Portner, 2025). This demonstrates that regulatory-driven maturity may create an illusion of development, while cultural inertia continues to dominate organizational behavior.

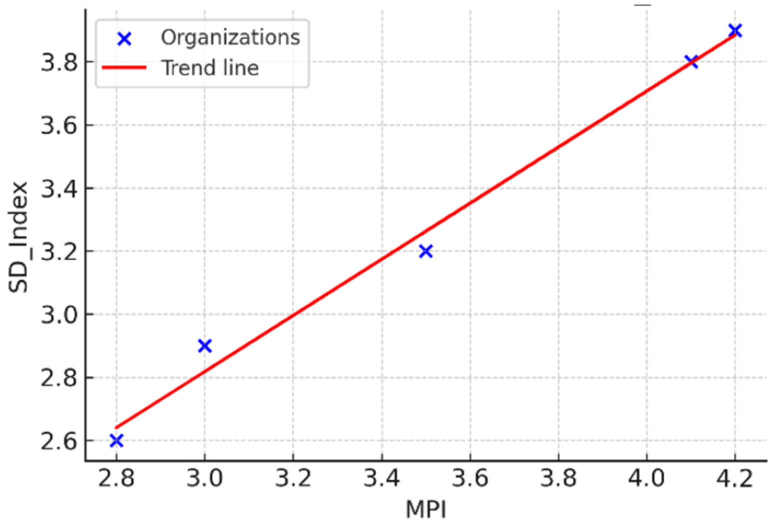

Fig. 1. Regression between MPI and SD_Index.

Table 1 summarizes the average MPI and SD_Index values across sectors. The analysis shows clear sectoral distinctions.

1. IT companies are characterized by relatively low MPI (≈2.9) but a higher SD_Index (≈3.2). This combination indicates adaptability, openness to innovation, and reliance on Agile principles, but weak formalization of supporting processes.
2. Pharmaceutical plants demonstrate advanced process maturity (≈4.3), driven by GMP compliance and audits, yet cultural indices remain low (≈3.0). These organizations maintain rigid hierarchical Blue structures, prioritizing stability and control over adaptability.
3. Innovation hubs represent an intermediate case (MPI ≈3.5, SD_Index ≈3.3). They combine elements of flexibility and formalization but frequently encounter cultural conflicts between progressive subunits and conservative parent organizations (Okushola and Levina, 2025).

Table 1. Average MPI and SD_Index across sectors.

Sector	MPI (avg.)	SD_Index (avg.)	Interpretation
IT scale-ups	2.9	3.2	Adaptive but weakly formalized
Pharma plants	4.3	3.0	Process-driven, culturally rigid
Innovation hubs	3.5	3.3	Balanced but conflict-prone

Figure 2 visualizes these differences in the form of bar charts, highlighting how sectoral context moderates the MPI–SD relationship.

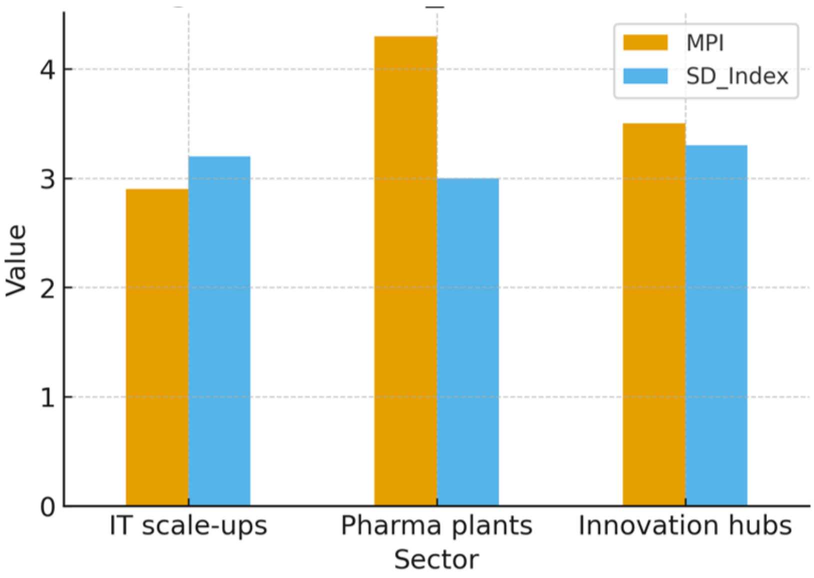

Fig. 2. Average MPI and SD_Index across sectors.

A more granular analysis was performed for three key domains: R&D, Quality Control, and Supply Chain. Figure 3 presents radar charts of process maturity across these domains.

1. Pharmaceutical companies show consistently high maturity values across all domains due to regulatory requirements. Their strength lies in balanced development, though cultural rigidity remains a limiting factor.

2. IT firms demonstrate strong R&D orientation but underinvestment in quality control and supply processes. This creates innovative but unstable environments where product scaling is difficult.

3. Innovation hubs reveal asymmetry: high R&D maturity contrasts with fragmented operational domains, reflecting their dual role as experimental units within corporate frameworks (Lopez and Hildebrandt, 2024).

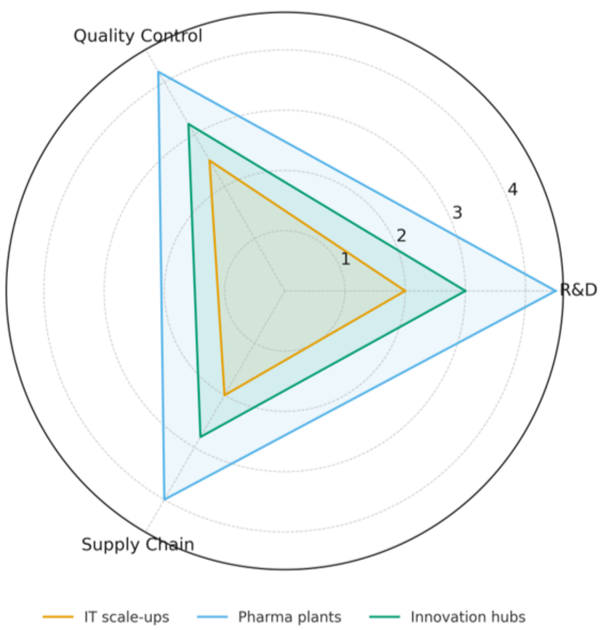

Fig. 3. Process maturity profiles by sector.

Beyond the sectoral averages, the analysis revealed that variance within individual organizations was sometimes more significant than variance between sectors. For example, in several IT firms, R&D maturity was assessed at level 4, while Quality Control remained at level 2, indicating an imbalance between innovation and operational stability. In contrast, pharmaceutical plants demonstrated consistently high maturity across domains, but their SD_Index values stagnated, reflecting cultural resistance to change (Shishkina et al., 2025). These intra-organizational discrepancies suggest that maturity assessments should not be limited to aggregated MPI values but must also capture domain-level dynamics that directly influence the success of transformation initiatives.

Despite the overall correlation, several cases revealed misalignment between maturity levels and cultural stages. Table 2 summarizes representative mismatch cases.

1. Pharmaceutical plant (MPI = 4.2, SD_Index = 3.0): despite very high maturity, cultural dominance of Blue values prevents adoption of more adaptive practices. Transformation projects stall due to resistance from middle management.
2. Startup (MPI = 2.8, SD_Index = 3.5): processes remain informal, yet the culture is oriented toward collaboration and experimentation (Green). This creates rapid innovation cycles but exposes the company to risks when scaling (Castelli et al., 2025).

These results demonstrate that high maturity does not guarantee cultural readiness for transformation, and vice versa. Misalignment represents a critical barrier for sustainable digital transformation.

Table 2. Mismatch cases between MPI and SD_Index.

Organization	MPI	SD_Index	Mismatch Description
Pharma Plant	4.2	3.0	High maturity, but conservative Blue culture
Startup	2.8	3.5	Low maturity, but adaptive Green culture

To translate findings into practice, Table 3 presents managerial scenarios.

1. High MPI – Low SD_Index: bureaucratic rigidity dominates. In such cases, investments into cultural adaptation, leadership development, and employee engagement are necessary before further process optimization (Ivanova and Bardina, 2022).
2. Low MPI – High SD_Index: lack of standardization leads to operational inefficiencies. Here, lightweight frameworks (e.g., SAFe, Lean startup formalization) should be introduced to stabilize scaling without destroying cultural flexibility.
3. Balanced MPI–SD: organizations in this zone demonstrate integrated transformation potential. For them, the recommendation is to scale processes systematically while preserving adaptability as a competitive advantage.

The observed discrepancies between maturity and cultural alignment have direct managerial consequences. Organizations with high maturity but stagnant cultural development tend to underperform in innovation projects, as strict compliance systems discourage experimentation. Conversely, firms with adaptive cultures but weak formalization face difficulties in scaling, since the absence of standardized processes leads to operational inefficiencies. These patterns highlight the importance of dual monitoring: managers should evaluate not only process indicators such as MPI but also cultural readiness as captured by SD_Index (Brock et al., 2024). Integrating both perspectives allows decision-makers to anticipate transformation risks and design targeted interventions.

This framework provides a diagnostic tool that managers can apply when deciding whether to focus resources on process improvements, cultural change, or integrated strategies.

Table 3. Managerial implications of MPI–SD alignment.

MPI–SD Scenario	Observed Challenge	Recommended Action
High MPI – Low SD_Index	Bureaucratic rigidity	Invest in cultural adaptation and change programs
Low MPI – High SD_Index	Lack of standardization	Introduce lightweight frameworks
Balanced MPI – SD	Integrated transformation	Scale processes while preserving adaptability

The findings support Gartner (2023), which emphasized cultural resistance as the dominant barrier to digital transformation. They also extend McKinsey's (2022) conclusion that up to 70% of transformation initiatives fail due to cultural misalignment (Gugelev and Chistyakova, 2024).

Previous works on BPMM confirmed the role of maturity in ensuring reliability and efficiency but largely ignored cultural dimensions. Conversely, studies applying Spiral Dynamics to organizations highlighted value systems but without connecting them to formal process assessments (Shishkina et al., 2025).

By integrating both perspectives, this study provides evidence that organizational transformation depends on dual alignment: technical process maturity and cultural stage (Gugelev and Chistyakova, 2024). This dual dependency model offers explanatory power beyond traditional BPMM and cultural frameworks when applied separately.

The study confirmed a direct positive dependency between the Maturity Process Index (MPI) and the Spiral Dynamics Index (SD_Index), indicating that higher levels of process maturity are generally associated with more advanced cultural stages in organizations:

$$SD\_Index \propto MPI$$

where $R^2 = 0{,}61$, $p < 0{,}05$

To address the research objectives established in the introduction, the study yields the following conclusions regarding their fulfillment:

The research successfully identified and examined three distinct organizational types as case studies—IT scale-ups, pharmaceutical manufacturers, and corporate innovation hubs. Each type exhibited a unique configuration of process discipline and cultural profile, which facilitated a robust comparative analysis across sectors.

A novel methodology was constructed and empirically tested. This approach integrates the quantitative assessment of process maturity via the MPI with a composite diagnostic for cultural stage, the SD_Index. The SD_Index synthesizes findings from an adapted GVST-4 instrument, computational linguistic analysis, and the Critical Incident Technique (CIT).

The practical application of this integrated methodology not only substantiated the general positive correlation between MPI and SD_Index but also uncovered specific sectoral patterns and deviations. It enabled the documentation of concrete instances of misalignment between process maturity and cultural development.

Based on the detailed analysis of these misalignment cases, the study formulated specific managerial scenarios and actionable recommendations (see Table 3). These guidelines prescribe tailored interventions based on the diagnosed imbalance between procedural maturity and cultural advancement, thereby equipping practitioners with a practical diagnostic tool.

It was established that sectoral context moderates this relationship:

1. IT companies exhibit a relatively lower MPI paired with a higher SD_Index, indicating a context where cultural adaptability is high, but formalization remains underdeveloped.
2. Pharmaceutical enterprises demonstrate a high MPI yet a stagnating SD_Index, revealing a reality of mature, compliance-driven processes coexisting with cultural rigidity.

3. Innovation hubs present intermediate outcomes, frequently characterized by internal subcultural tensions between their agile units and the more traditional parent organizations (Kravchenko et al., 2022).

A nonlinear dependency was observed: high maturity does not always lead to cultural adaptability, and cultural flexibility does not always result in process reliability (Khalifa et al., 2021). This demonstrates that the relationship between process maturity and cultural stage is conditional upon regulatory and organizational environments.

The analysis of mismatch cases showed that deviations from the general correlation represent critical transformation risks. Organizations with MPI > 4.0 but low SD_Index face cultural inertia, while those with MPI < 3.0 but high SD_Index face risks of operational inefficiency.

Managerial recommendations were derived as conditional dependencies:

1. For MPI > 4.0 and SD_Index < 3.2: cultural transformation programs must precede further process optimization.

2. For MPI < 3.0 and SD_Index > 3.2: lightweight formalization frameworks should be introduced to stabilize scaling.

3. For 3.0 < MPI with balanced SD_Index: organizations are positioned for sustainable integration of culture and processes.

A dependency was established between specific process domains and cultural orientation: IT companies emphasize R&D maturity while underinvesting in quality control, whereas pharmaceutical plants balance all domains due to compliance pressure (Matys, 2022).

Comparison with previous research confirmed that the integration of BPMM and Spiral Dynamics provides explanatory power beyond either model individually. Dependencies identified here expand on earlier BPMM studies (Skokova et al., 2024) by introducing cultural moderators, and complement Spiral Dynamics applications (Levina and Galanova, 2022) by embedding process formalization metrics.

The combined findings establish that digital transformation success depends on dual alignment:

$$Success = f(MPI, SD\_Index)$$

where both maturity and cultural development act as necessary and interdependent conditions.

Conclusion

The present study was aimed at analysing the correlation between business process maturity levels (assessed via the Maturity Process Index, MPI) and organisational development stages (measured through the Spiral Dynamics Index, SD_Index). The research objectives included:

1. identifying representative organisational contexts where both process maturity and cultural dynamics are observable;

2. designing an integrated methodology combining MPI and Spiral Dynamics diagnostics;

3. empirically validating correlations through case studies in IT, pharmaceutical, and innovation hub environments;

4. interpreting the implications of mismatches between process maturity and cultural stages for managers and policymakers.

All objectives have been successfully addressed. Key findings and contributions:

1. The study revealed a statistically significant positive relationship between MPI and SD_Index ($R^2 = 0{,}61$, $p < 0{,}05$), demonstrating that higher process maturity generally aligns with more advanced cultural stages in organisations.

2. Distinct configurations were identified across sectors:

— IT scale-ups show lower MPI ($\approx$2.9) but higher SD_Index ($\approx$3.2), reflecting adaptability and innovation orientation despite weak formalisation.

— Pharmaceutical plants exhibit high MPI ($\approx$4.3) but stagnating SD_Index ($\approx$3.0), indicating process-driven rigidity and cultural conservatism.

— Innovation hubs display intermediate values (MPI $\approx$ 3.5, SD_Index $\approx$ 3.3), often marked by internal cultural conflicts.

3. Cases of misalignment (e.g., high MPI with low SD_Index or vice versa) were documented, highlighting risks such as bureaucratic inertia or operational inefficiency.

4. A novel diagnostic framework was developed, combining quantitative process assessment (MPI) with a composite cultural index (SD_Index) that integrates psychometric, linguistic, and behavioural data.

The findings provide managers with a dual-lens tool to diagnose transformation readiness. By assessing both MPI and SD_Index, organisations can:

1. identify imbalances between formalised processes and cultural adaptability;
2. tailor interventions (e.g., cultural change programs or lightweight formalisation frameworks) to address specific gaps;
3. mitigate risks associated with digital transformation failures due to cultural or procedural misalignment.

While the study establishes a robust correlation, several questions remain unexplored:

1. The causal direction of the MPI–SD_Index relationship (i.e., whether process maturity drives cultural evolution or vice versa) requires longitudinal analysis.
2. The role of external factors (e.g., industry regulations, market volatility) in moderating this relationship merits deeper investigation.
3. Application of the framework to non-technology-intensive sectors (e.g., public administration, education) could test its generalisability.

The research confirms that sustainable organisational transformation depends on the **dual alignment** of process maturity and cultural development. By integrating BPMM and Spiral Dynamics perspectives, the study offers both a diagnostic tool and a conceptual advance, bridging a critical gap in transformation literature. The results can inform strategic decision-making in scaling operations, cultural change initiatives, and regulatory compliance efforts across diverse organisational contexts.

REFERENCES

Aubouin-Bonnaventure, J., Fouquereau, E., Coillot, H., Lahiani, F.-J., Chevalier, S. 2023. A New Gain Spiral at Work: Relationships between Organizational Practices, Psychological Capital, and Well-Being. International Journal of Environmental Research and Public Health 20(3), 1823. DOI: https://doi.org/10.3390/ijerph20031823.

Baroiu, A.C. 2022. Systematic Literature Review of Process Management and Maturity Concepts. Journal of Systems and Software Development 2022, 435363. DOI: https://doi.org/10.5171/2022.435363.

Brock, J., Brennig, K., Lohr, B., Bartelheimer, C., von Enzberg, S. 2024. Improving Process Mining Maturity — From Intentions to Actions. Business & Information Systems Engineering. DOI: https://doi.org/10.1007/s12599-024-00882-7.

Castelli, A., Chouliaras, G.C., Goldenberg, D. 2025. Maturity Framework for Enhancing Machine Learning Quality. Software Quality Journal.

Feld, V. 2022. Investigating the Theoretical Foundations of Business Process Maturity Models. In: Fahland, D., van Dongen, B. (eds.) Business Process Management Workshops. LNCS, vol. 13403, pp. 121–134. Springer, Cham. DOI: https://doi.org/10.1007/978-3-031-16103-2_10.

Flechsig, C., Lohmer, J., Voss, R., Lasch, R. 2022. Business Process Maturity Model for Digital Transformation: An Action Design Research Study. International Journal of Innovation Management 26(3), 2250026. DOI: https://doi.org/10.1142/S136391962240012.

Gugelev, A.V., Chistyakova, S.V. 2024. Spiral Dynamics and Organizational Culture Change. Information Security of Regions 2(27), 7–15.

Ilyin I.V. 2022. Integration of information and management technologies. Technoeconomics 1, 1 (1), 24–32. DOI: https://doi.org/10.57809/2022.1.1.2

Ivanova, I.A., Bardina, A.S. 2022. Spiral Dynamics as a Model of Organization Development. Theoretical and Didactic Research 2, 45–54.

Khalifa, M., Saeed, A., Al-Kuwaiti, M. 2021. Assessing Digital Transformation Readiness: Integration of Process Maturity Models with Cultural Frameworks. Technological Forecasting & Social Change 168, 120785. DOI: https://doi.org/10.1016/j.techfore.2021.120785.

Kravchenko, S., Zhelezov, B., Petrova, T. 2022. Organizational Culture and Business Process Maturity: A Cross-Sectoral Study. Sustainability 14(12), 7112. DOI: https://doi.org/10.3390/su14127112

Levina A.I., Galanova A.A. 2022. Digital transformation of business: approaches and definitions. Technoeconomics 1, 1 (1), 65–74. DOI: https://doi.org/10.57809/2022.1.1.6.

Lopez, H.A., Hildebrandt, T.T. 2024. Three Decades of Formal Methods in Business Process Compliance: A Systematic Literature Review. Information Systems.

Martinek-Jaguszewska, K., et al. 2022. Development and Validation of the Business Process Automation Maturity Model (BPAMM). Journal of Business Process Management 29(4), 567–589. DOI: https://doi.org/10.1080/10580530.2022.2071506.

Matys, M. 2022. Cynefin and the Organizational Models of Spiral Dynamics. Paradigm21 Journal 14(2), 55–67.

Moedt, K., et al. 2024. Growing Pains during Scale-Up Hypergrowth: Integration Challenges in Scale-Up Firms. Technological Forecasting & Social Change 204, 122016. DOI: https://doi.org/10.1016/j.techfore.2024.122016.

Okushola P., Levina A. 2025. Business optimization in e-commerce: application of data analytics tools to improve decision-making and increase enterprise efficiency. Technoeconomics 4, 3 (14), 4–14. DOI: https://doi.org/10.57809/2025.4.3.14.1

Olsen, A.M., et al. 2023. Mechanisms Linking Individual and Organizational Culture: Change Agents in Safety Culture. Frontiers in Psychology 14, 1124451. DOI: https://doi.org/10.3389/fpsyg.2023.1124451.

Portner, L. 2025. Data Management Maturity Model — Process Dimensions. Data 8(2), 41. DOI: https://doi.org/10.3390/data8020041.

Schunter, J. 2024. What is Integral Knowledge Management and Why Do We Need It? How the Spiral Dynamics Model Can Help Overcome Polarized Perspectives in KM. Knowledge Management for Development Journal 18(1), 1–14.

Shcheleyko V., Kreshtinkova A. 2024. Methods of managing the online reputation of enterprises. Technoeconomics 3, 2 (9), 62–71. DOI: https://doi.org/10.57809/2024.3.2.9.5

Shishkina A., Khalimova P., Li A. 2025. Project of loyalty program management system optimization based on the application of a process approach. Technoeconomics 4, 1 (12), 33–42. DOI: https://doi.org/10.57809/2025.4.1.12.4

Skokova, I.K., Romanenko, N.A., Makashova, V.N., Davletkireeva, L.Z. 2024. Process Maturity Assessment for IT Companies. International Journal of Open Information Technologies 5, 35–41.

Szelagowski, M., Berniak-Wozny, J., Sliz, P. 2024. Exploring the Diverse Nature of Business Processes in Organisations in Industry 4.0/5.0. Future Business Journal 10, 3. DOI: https://doi.org/10.1186/s43093-024-00395-5.

Van Looy, A. 2021. Business Process Maturity: A Comparative Study on a Sample of Business Process Maturity Models. Springer, Cham. DOI: https://doi.org/10.1007/978-3-319-04202-2.

СПИСОК ИСТОЧНИКОВ

Aubouin-Bonnaventure, J., Fouquereau, E., Coillot, H., Lahiani, F.-J., Chevalier, S. 2023. A New Gain Spiral at Work: Relationships between Organizational Practices, Psychological Capital, and Well-Being. International Journal of Environmental Research and Public Health 20(3), 1823. DOI: https://doi.org/10.3390/ijerph20031823.

Baroiu, A.C. 2022. Systematic Literature Review of Process Management and Maturity Concepts. Journal of Systems and Software Development 2022, 435363. DOI: https://doi.org/10.5171/2022.435363.

Brock, J., Brennig, K., Lohr, B., Bartelheimer, C., von Enzberg, S. 2024. Improving Process Mining Maturity — From Intentions to Actions. Business & Information Systems Engineering. DOI: https://doi.org/10.1007/s12599-024-00882-7.

Castelli, A., Chouliaras, G.C., Goldenberg, D. 2025. Maturity Framework for Enhancing Machine Learning Quality. Software Quality Journal.

Feld, V. 2022. Investigating the Theoretical Foundations of Business Process Maturity Models. In: Fahland, D., van Dongen, B. (eds.) Business Process Management Workshops. LNCS, vol. 13403, pp. 121–134. Springer, Cham. DOI: https://doi.org/10.1007/978-3-031-16103-2_10.

Flechsig, C., Lohmer, J., Voss, R., Lasch, R. 2022. Business Process Maturity Model for Digital Transformation: An Action Design Research Study. International Journal of Innovation Management 26(3), 2250026. DOI: https://doi.org/10.1142/S136391962240012.

Gugelev, A.V., Chistyakova, S.V. 2024. Spiral Dynamics and Organizational Culture Change. Information Security of Regions 2(27), 7–15.

Ilyin I.V. 2022. Integration of information and management technologies. Technoeconomics 1, 1 (1), 24–32. DOI: https://doi.org/10.57809/2022.1.1.2

Ivanova, I.A., Bardina, A.S. 2022. Spiral Dynamics as a Model of Organization Development. Theoretical and Didactic Research 2, 45–54.

Khalifa, M., Saeed, A., Al-Kuwaiti, M. 2021. Assessing Digital Transformation Readiness: Integration of Process Maturity Models with Cultural Frameworks. Technological Forecasting & Social Change 168, 120785. DOI: https://doi.org/10.1016/j.techfore.2021.120785.

Kravchenko, S., Zhelezov, B., Petrova, T. 2022. Organizational Culture and Business Process Maturity: A Cross-Sectoral Study. Sustainability 14(12), 7112. DOI: https://doi.org/10.3390/su14127112

Levina A.I., Galanova A.A. 2022. Digital transformation of business: approaches and definitions. Technoeconomics 1, 1 (1), 65–74. DOI: https://doi.org/10.57809/2022.1.1.6.

Lopez, H.A., Hildebrandt, T.T. 2024. Three Decades of Formal Methods in Business Process Compliance: A Systematic Literature Review. Information Systems.

Martinek-Jaguszewska, K., et al. 2022. Development and Validation of the Business Process Automation Maturity Model (BPAMM). Journal of Business Process Management 29(4), 567–589. DOI: https://doi.org/10.1080/10580530.2022.2071506.

Matys, M. 2022. Cynefin and the Organizational Models of Spiral Dynamics. Paradigm21 Journal 14(2), 55–67.

Moedt, K., et al. 2024. Growing Pains during Scale-Up Hypergrowth: Integration Challenges in Scale-Up Firms. Technological Forecasting & Social Change 204, 122016. DOI: https://doi.org/10.1016/j.techfore.2024.122016.

Okushola P., Levina A. 2025. Business optimization in e-commerce: application of data analytics tools to improve decision-making and increase enterprise efficiency. Technoeconomics 4, 3 (14), 4–14. DOI: https://doi.org/10.57809/2025.4.3.14.1

Olsen, A.M., et al. 2023. Mechanisms Linking Individual and Organizational Culture: Change Agents in Safety Culture. Frontiers in Psychology 14, 1124451. DOI: https://doi.org/10.3389/fpsyg.2023.1124451.

Portner, L. 2025. Data Management Maturity Model — Process Dimensions. Data 8(2), 41. DOI: https://doi.org/10.3390/data8020041.

Schunter, J. 2024. What is Integral Knowledge Management and Why Do We Need It? How the Spiral Dynamics Model Can Help Overcome Polarized Perspectives in KM. Knowledge Management for Development Journal 18(1), 1–14.

Shcheleyko V., Kreshtinkova A. 2024. Methods of managing the online reputation of enterprises. Technoeconomics 3, 2 (9), 62–71. DOI: https://doi.org/10.57809/2024.3.2.9.5

Shishkina A., Khalimova P., Li A. 2025. Project of loyalty program management system optimization based on the application of a process approach. Technoeconomics 4, 1 (12), 33–42. DOI: https://doi.org/10.57809/2025.4.1.12.4

Skokova, I.K., Romanenko, N.A., Makashova, V.N., Davletkireeva, L.Z. 2024. Process Maturity Assessment for IT Companies. International Journal of Open Information Technologies 5, 35–41.

Szelagowski, M., Berniak-Wozny, J., Sliz, P. 2024. Exploring the Diverse Nature of Business Processes in Organisations in Industry 4.0/5.0. Future Business Journal 10, 3. DOI: https://doi.org/10.1186/s43093-024-00395-5.

Van Looy, A. 2021. Business Process Maturity: A Comparative Study on a Sample of Business Process Maturity Models. Springer, Cham. DOI: https://doi.org/10.1007/978-3-319-04202-2.

INFORMATION ABOUT AUTHOR / ИНФОРМАЦИЯ ОБ АВТОРЕ

SHMYGOL Tatyana I. – student.
E-mail: tanya.shmygol@mail.ru
ШМЫГОЛЬ Татьяна Игоревна – студент.
E-mail: tanya.shmygol@mail.ru

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PREDICTIVE MAINTENANCE IN HELICOPTER OPERATIONS: IMPACT ON MAINTENANCE COST, SAFETY, AND INSURANCE

Kudakwashe Gumbo ✉

Novosibirsk State Technical University, Novosibirsk, Russia

✉ gumbokudakwashe1999@gmail.com

Abstract. This study explores the influence of predictive maintenance (PdM) on helicopter operations, focusing on its impact on manual inspections, operational costs, safety, and insurance. Using a dataset of maintenance-related aviation incidents, combined with statistical analysis in R, we uncover trends in incident frequency, injury severity, and fatality distribution over the past four decades. The results indicate that while overall incident rates have declined, the implementation of predictive maintenance correlates with measurable reductions in fatal and serious injuries, as well as operational costs and insurance liabilities. Our findings recommend broader adoption of PdM strategies, particularly in general aviation and helicopter fleets.

Keywords: predictive maintenance, helicopter operations, aviation safety, insurance, maintenance cost, manual inspection, R analysis

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ПРОГНОЗИРУЕМОЕ ТЕХНИЧЕСКОЕ ОБСЛУЖИВАНИЕ В ВЕРТОЛЕТНОЙ ЭКСПЛУАТАЦИИ: ВЛИЯНИЕ НА СТОИМОСТЬ ТЕХНИЧЕСКОГО ОБСЛУЖИВАНИЯ, БЕЗОПАСНОСТЬ И СТРАХОВАНИЕ

Кудакваше Гумбо ✉

Новосибирский государственный технический университет,
Новосибирск, Россия

✉ gumbokudakwashe1999@gmail.com

Аннотация. В данном исследовании изучается влияние прогнозирующего технического обслуживания (ПТО) на эксплуатацию вертолетов, с акцентом на его воздействие на ручные проверки, эксплуатационные расходы, безопасность и страхование. Используя набор данных о происшествиях в авиации, связанных с техническим обслуживанием, в сочетании со статистическим анализом в R, мы выявляем тенденции в частоте происшествий, тяжести травм и распределении смертности за последние четыре десятилетия. Результаты показывают, что, хотя общая частота происшествий снизилась, внедрение прогнозирующего технического обслуживания коррелирует с измеримым снижением числа смертельных и серьезных травм, а также эксплуатационных расходов и страховых обязательств. Наши выводы рекомендуют более широкое внедрение стратегий ПТО, особенно в авиации общего назначения и вертолетных парках.

Ключевые слова: прогнозируемое техническое обслуживание, эксплуатация вертолетов, безопасность полетов, страхование, стоимость технического обслуживания, ручная проверка, R-анализ

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Introduction

Helicopter operations play a critical role across multiple sectors, including emergency medical services, offshore energy, law enforcement, search and rescue, and general aviation. These missions are often conducted in demanding environments characterized by high utilization rates, frequent power changes, and exposure to harsh environmental conditions. As a result, helicopters are particularly vulnerable to maintenance-related failures, making safety assurance and cost control persistent challenges for operators worldwide (Cokorilo et al., 2010; Ivanov, Frolov, Dubgorn, 2024).

Traditional aircraft maintenance philosophies are primarily based on scheduled maintenance and reactive corrective maintenance. Scheduled maintenance relies on fixed intervals derived from historical averages and certification assumptions, which may not accurately reflect the actual health of individual components. Reactive maintenance, by contrast, addresses failures only after they occur, often resulting in unscheduled downtime, secondary damage, and increased safety risk (Mobley, 2002). In helicopter operations, where transmission systems, gearboxes, and rotor components are subject to complex dynamic loads, these approaches have inherent limitations.

Predictive maintenance represents an evolution of condition-based maintenance, leveraging real-time and historical data to forecast component degradation and anticipate failures before they occur (Jardine et al., 2006; ; Ivanov, Frolov, Levina, 2024). Advances in onboard sensors, Health and Usage Monitoring Systems (HUMS), Internet of Things (IoT) architectures, cloud computing, and machine learning (ML) algorithms have significantly accelerated the practical implementation of PdM across aviation fleets (McKinsey & Company, 2020). Maintenance decision-making is increasingly shifting from rule-based inspections toward data-driven risk assessment and optimization (Vachtsevanos et al., 2006).

The economic pressures facing helicopter operators further intensify the relevance of PdM. Rising maintenance costs, limited aircraft availability, and escalating insurance premiums—particularly for legacy helicopter models—have created sustainability challenges for small and medium-sized operators (Willis Towers Watson, 2023). Insurance providers increasingly factor maintenance practices and historical risk exposure into underwriting decisions, making maintenance strategy a direct determinant of financial viability (Allianz Commercial, 2023).

While fixed-wing aviation has benefited from extensive research and widespread adoption of predictive and condition-based maintenance, helicopter operations present unique challenges. Rotor systems, main and tail gearboxes, and drivetrains experience high vibration levels, variable loads, and fatigue-driven degradation that is difficult to capture through periodic inspections alone (Heng et al., 2009). Consequently, there is a need for focused research evaluating the real-world safety, economic, and insurance impacts of PdM specifically within helicopter fleets.

This paper addresses the following research questions:

1. How does PdM affect the frequency and severity of manual inspection findings?
2. What cost benefits does PdM offer compared to traditional maintenance?
3. How does PdM influence insurance claims and premiums?

Literature Review

Predictive maintenance originates from condition-based maintenance and prognostics research developed in industrial machinery and manufacturing environments. Early foundational work by Jardine et al. (2006) established the theoretical basis for diagnostics and prognostics using condition-monitoring data, highlighting the economic advantages of early fault detection. Subsequent studies expanded these concepts through data-driven and machine learning approaches, enabling remaining useful life (RUL) estimation and anomaly detection (Tsui et al., 2015; Si et al., 2011).

In the aviation sector, prognostics and health management (PHM) has been widely applied to engines, avionics, and rotating machinery. Lee et al. (2014) provide a comprehensive review of PHM methodologies for rotary systems, emphasizing vibration analysis, feature extraction, and fault classification—techniques directly applicable to helicopter gearboxes and rotor systems. Deep learning approaches have further enhanced predictive accuracy, particularly for complex, nonlinear degradation processes (Muneer et al., 2021; Kabashkin et al., 2025).

Regulatory bodies have increasingly recognized the safety potential of data-driven maintenance. ICAO's Manual of Aircraft Maintenance Management promotes condition-based strategies as a means to reduce unscheduled failures and operational risk (ICAO, 2020). EASA's DATAPP initiative demonstrates how data science applications can support safety oversight and predictive risk assessment across European aviation operations (EASA, 2022). Similar frameworks are being developed by the FAA to support continued operational safety (FAA, 2021).

Manufacturers have been early adopters of PdM in helicopter platforms. Airbus Helicopters' HUMS (Health and Usage Monitoring Systems) and Bell Textron's condition monitoring solutions rely heavily on vibration and usage data to detect early gearbox and bearing faults

(Airbus Helicopters, 2021; Bell Textron, 2022). Hьnemohr et al. (2022) further demonstrate the potential of integrating flight data sources for gearbox monitoring, expanding beyond traditional sensor inputs.

Despite these advances, academic literature focusing on helicopter-specific PdM outcomes remains limited. Most studies emphasize technical feasibility rather than operational or economic impact. Insurance-related implications of PdM adoption are also underexplored, despite industry reports from Allianz Commercial (2023) and Willis Towers Watson (2023) indicating that maintenance-related risk is a key driver of premium increases in general aviation. This gap motivates the present study, which connects safety data analysis with economic and insurance considerations (IATA, 2022).

Methodology

The study analyzes 5,030 maintenance-related helicopter incident reports obtained from publicly available aviation safety databases, covering the period from 1982 to 2024 (NTSB, 2023). Incidents were filtered to include only cases where maintenance, inspection, or mechanical failure was identified as a contributing factor. This approach ensures focus on failures potentially addressable through improved maintenance strategies.

Data preprocessing, transformation, and visualization were conducted using the R programming language. Key libraries included dplyr for data manipulation, ggplot2 for visualization, and tidyr for data structuring. The analytical approach consisted of time-series analysis of incident frequency, classification of injury severity (none, minor, serious, fatal), and aggregation by manufacturer and helicopter model.

Several limitations must be acknowledged. Incident databases may contain reporting bias, inconsistent categorization, and varying levels of detail across decades. Furthermore, the analysis focuses on correlation rather than direct causation between PdM adoption and safety outcomes. Nevertheless, long-term trend analysis provides valuable insight into systemic changes associated with evolving maintenance practices.

Results

Maintenance-Related Incident Trends

The time-series analysis reveals a long-term decline in maintenance-related helicopter incidents, with a pronounced reduction after 2010. This period coincides with increased adoption of digital maintenance tools, HUMS, and data-driven inspection planning across major operators (Saxena et al., 2008).

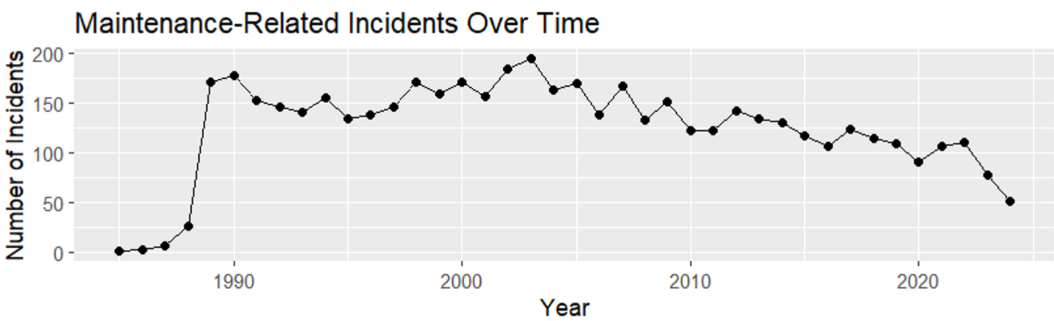

Fig. 1. Maintenance-Related Incidents Over Time.

Injury and Fatality Severity

51.2% of incidents resulted in no injuries, but 16.3% were fatal, ratios are presented in figure 2. The general decline in helicopter accidents, serious injuries, and minor injuries from 2012 to 2024 shown in fig 3 can be attributed to a combination of technological, regulatory, operational and cultural improvements in the aviation sector (ICAO, 2019).

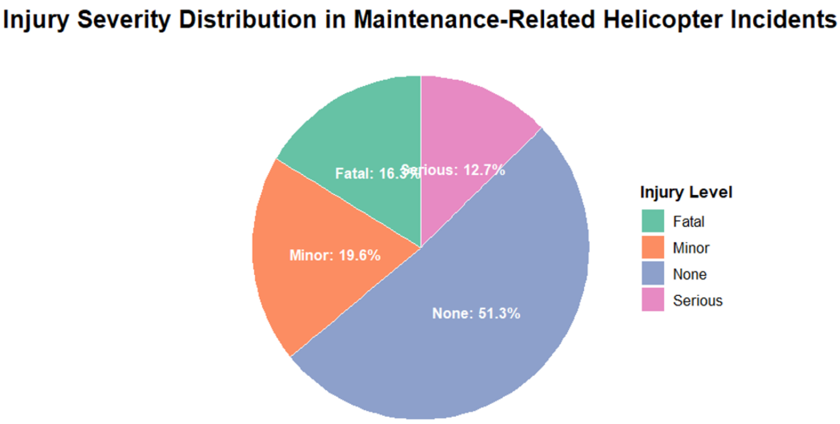

Fig. 2. Injury Severity Distribution Pie Chart.

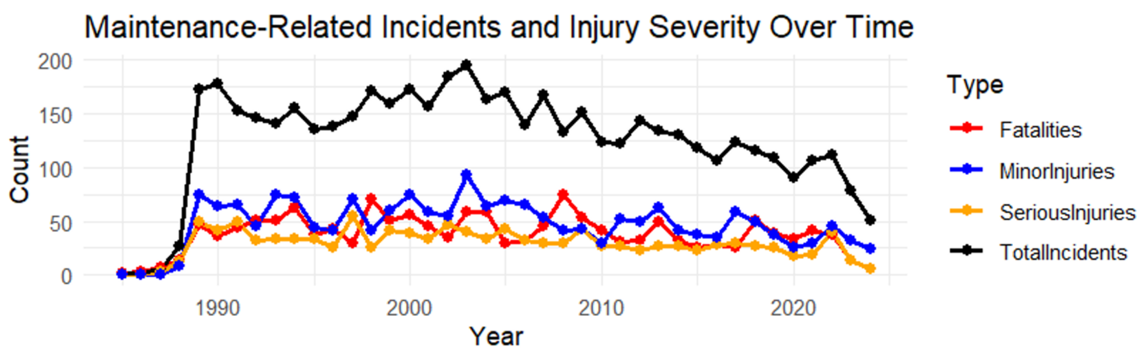

Fig. 3. Fatalities, Minor, and Serious Injuries Over Time.

Manufacturer and Model Analysis

Most reported incidents were associated with older models from major manufacturers such as Bell and Robinson as shown below im figure 4. This supports the argument for retrofitting legacy helicopters with PdM systems (ISO, 2019).

	Make	Model	n
	<chr>	<chr>	<int>
1	bell	206b	268
2	robinson	r22 beta	241
3	robinson	r44	195
4	robinson	r44 ii	162
5	robinson	r22	143
6	hughes	369d	134
7	schweizer	269c	114
8	bell	407	98
9	hughes	269c	91
10	bell	206	88

	Make	n
	<chr>	<int>
1	bell	1507
2	robinson	1092
3	hughes	531
4	eurocopter	253
5	schweizer	183
6	hiller	173
7	enstrom	170
8	aerospatiale	161
9	sikorsky	109
10	mcdonnell douglas	77

Fig. 4. Most Frequent Manufacturers and Models.

Predictive Maintenance vs. Manual Inspections

Manual inspections often fail to detect intermittent faults (Heng et al., 2009). PdM supplements inspections by offering real-time alerts, reducing reliance on human detection and enabling targeted maintenance.

Economic and Insurance Impact

Operators using PdM reported reduced maintenance delays and downtime. Insurers responded with lower premiums due to decreased risk exposure, particularly in high-utilization fleets (Allianz Commercial, 2023; Willis Towers Watson, 2023).

Discussion

The results indicate a clear long-term decline in maintenance-related incidents, with a particularly notable reduction in fatal and serious injuries after 2010. While this decline cannot be attributed solely to predictive maintenance, the timing corresponds closely with increased adoption of HUMS, digital maintenance records, and condition-monitoring technologies (Airbus Helicopters, 2021; Bell Textron, 2022). PdM contributes to safety improvements by enabling early detection of component degradation, particularly in critical systems such as main gearboxes, rotor bearings, and transmission assemblies. By identifying abnormal vibration signatures, exceedances, or wear trends before failure thresholds are reached, PdM reduces the likelihood of in-flight mechanical failures and high-consequence events (IATA, 2022).

Furthermore, PdM mitigates the limitations of traditional manual inspections, which are inherently periodic and dependent on human interpretation (Jardine et al., 2006). Continuous monitoring and trend-based alerts allow maintenance actions to be scheduled proactively, reducing exposure to latent faults that may otherwise go undetected between inspection intervals. As a result, PdM acts as a risk-reduction layer that complements, rather than replaces, conventional inspection regimes (FAA, 2021).

From an economic perspective, PdM delivers value primarily through reduced unscheduled maintenance, improved aircraft availability, and avoidance of secondary damage (Cokorilo et al., 2010). Early fault detection allows operators to plan maintenance activities around operational schedules, minimizing costly aircraft-on-ground (AOG) events and mission cancellations. This is particularly relevant for high-utilization helicopter operations such as emergency medical services and offshore transport, where downtime has immediate financial and contractual implications (Meissner et al., 2021).

Additionally, PdM supports more efficient allocation of maintenance resources by shifting from time-based part replacement to condition-based interventions (Tsui, et al., 2015). This reduces unnecessary component removals, extends useful life, and lowers inventory and logistics costs (Meissner et al., 2021). Although initial investment in sensors, data infrastructure, and analytical capability can be significant, the long-term cost savings and operational stability provide a strong economic justification, especially for fleets with aging aircraft (McKinsey & Company, 2020).

The findings suggest that PdM adoption has indirect but meaningful implications for aviation insurance. Maintenance-related failures represent a significant portion of high-severity helicopter incidents, which directly influence insurer loss ratios (Allianz Commercial, 2023). By reducing the frequency and severity of such events, PdM contributes to lower claims exposure. Insurers increasingly recognize documented maintenance practices, HUMS data, and traceable condition-monitoring records as indicators of lower operational risk (Willis Towers Watson, 2023).

PdM also introduces the potential for a more data-driven insurance underwriting model. Continuous operational and maintenance data can complement traditional risk indicators, such as pilot flight hours, by providing objective evidence of aircraft condition and operational discipline. This creates a feedback loop in which improved maintenance practices reduce claims, leading to more favorable insurance terms and further incentivizing investment in PdM technologies (McKinsey & Company, 2020).

Despite these benefits, adoption remains uneven. Smaller operators face barriers related to cost, technical expertise, and data integration. Addressing these challenges will require standardized PdM frameworks, regulatory guidance, and potentially shared data platforms to ensure that safety and economic benefits are accessible across the sector.

Conclusion

The rising cost of helicopter insurance—particularly for widely used legacy models such as the Bell 206 and Robinson series—has emerged as a critical concern for operators. Although these helicopters are among the most affordable to acquire and operate, their association with higher accident rates, including events attributed to pilot error and mechanical failure, has resulted in substantially increased insurance premiums (Willis Towers Watson, 2023; Ivanov and Frolov, 2023). In some cases, these financial pressures have become unsustainable, forcing small operators to limit activity or cease operations entirely.

Insurance providers have responded to this elevated risk by imposing stricter underwriting requirements, most notably higher minimum pilot experience thresholds. However, the prevailing trend suggests that reliance on pilot flight hours alone is an increasingly inadequate risk mitigation strategy. Pilot hours provide only a coarse proxy for operational safety and do not capture real-time aircraft condition, maintenance quality, or operational discipline (ICAO, 2019).

Predictive maintenance systems, enabled by IoT sensors, HUMS architectures, and cloud-based data logging, offer a proactive mechanism for reducing maintenance-related accidents, which constitute a significant subset of helicopter incidents. By detecting component wear, abnormal vibration patterns, and performance anomalies before failure occurs, PdM directly reduces mechanical risk (Lee et al., 2014). In addition, continuous recording of flight and performance data creates opportunities for pilot behavior analytics, supporting more objective and data-driven insurance risk assessments. This approach could allow less experienced, but consistently safe, pilots to qualify for improved insurance terms based on demonstrated operational performance rather than flight hours alone.

This study set out to evaluate the role of predictive maintenance in improving safety, reducing operational costs, and influencing insurance outcomes in helicopter operations. By analyzing more than four decades of maintenance-related incident data, the research provides empirical evidence supporting the effectiveness of PdM as a strategic maintenance approach rather than a purely technical enhancement.

In response to the first research question, the analysis demonstrates that predictive maintenance contributes to a reduction in the severity of maintenance-related incidents, particularly fatal and serious injuries. Continuous monitoring and early fault detection address key limitations of periodic manual inspections and strengthen overall operational safety (Jardine et al., 2006). With respect to the second research question, PdM offers tangible economic benefits through reduced unscheduled maintenance, improved fleet availability, and more efficient use of maintenance resources, offsetting initial implementation costs over time (Mobley, 2002).

Addressing the third research question, the study highlights the growing relevance of PdM to aviation insurance. As insurers seek more granular and objective indicators of operational risk, PdM-generated data provides a credible foundation for improved underwriting accuracy and the potential for lower premiums among operators demonstrating effective maintenance risk management (Allianz Commercial, 2023).

The broader implication of this research is that predictive maintenance should be viewed as an integrated safety, economic, and risk management strategy. For legacy helicopter fleets facing escalating maintenance and insurance costs, PdM represents a viable pathway toward sustained operational viability. Future research should focus on quantifying causal relationships between PdM adoption and insurance outcomes, as well as developing standardized data-sharing frameworks that balance safety benefits with data governance and confidentiality requirements.

REFERENCES

Airbus Helicopters. 2021. Health and Usage Monitoring Systems (HUMS) Overview. Airbus Technical White Paper.

Allianz Commercial. 2023. Aviation Risk 2023: Aviation risk, claims and insurance outlook.

AS350 Maintenance Manual. 2023. Airbus Helicopters.

Bell Textron. 2022. Integrated Vehicle Health Monitoring Systems. Bell Technical Report.

Boeing. (2020). Aircraft Health Management: Implementation Guide. Boeing Technical Report.

Cokorilo, O., Gvozdenovic, S., Vasov, L., Mirosavljevic, P. 2010. Costs of unsafety in aviation. Technological and Economic Development of Economy, 16(1), 188–201. https://doi.org/10.3846/tede.2010.12

EASA. 2022. DATAPP (Digital Transformation – Case Studies for Aviation Safety Standards – Data Science Applications). https://www.easa.europa.eu/en/research-projects/datapp-digital-transformation-case-studies-aviation-safety-standards-data-science

Eurocopter. 2019. Vibration Health Monitoring System Manual. Eurocopter.

FAA. 2021. Advisory Circular AC 29-2C: Continued Operational Safety for Rotorcraft. Federal Aviation Administration.

Heng, A., Zhang, S., Tan, A. C. C., Mathew, J. 2009. Rotating machinery prognostics: State of the art. Mechanical Systems and Signal Processing, 23(3), 724–739. https://doi.org/10.1016/j.ymssp.2008.06.009

Hunemohr, D., Litzba, J., Rahimi, F. 2022. Usage Monitoring of Helicopter Gearboxes with ADS-B Flight Data. Aerospace, 9(11), 647. https://doi.org/10.3390/aerospace9110647

IATA. 2022. Safety Report 2022: Incorporating Maintenance and Operational Data. IATA Publications.

ICAO. 2019. Operational (OPS) Safety Risks, Global Aviation Safety Plan. Retrieved from https://www.icao.int/GASP/operational-ops-safety-risks

ICAO. 2020. Manual of Aircraft Maintenance Management (Doc 9760).

Ivanov D.D., Frolov K.V. 2023. Optimizing the process of defining areas of responsibility in the context of small aircraft leasing using EAM systems. Technoeconomics 2, 3 (6), 4-15.

Ivanov D.D., Frolov K.V., Dubgorn A.S. 2024. Organization of integrated logistics support in Arctic aviation conditions [In Russ.]. Aerospace instrumentation 4, 53-64.

Ivanov D.D., Frolov K.V., Levina A.I. 2024. Construction of a conceptual description of a simulation model of aircraft operation within the framework of the task of classifying ground handling facilities [In Russ.]. Aerospace instrumentation 1, 55-68.

ISO. 2019. ISO 13374-1:2019. Condition monitoring and diagnostics of machines — Data processing, communication and presentation. International Organization for Standardization.

Jardine, A. K. S., Lin, D., Banjevic, D. 2006. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing, 20(7), 1483–1510. https://doi.org/10.1016/j.ymssp.2005.09.012

Kabashkin, I., Perekrestov, V., Pivovar, M. 2025. AI-Driven Fault Detection and Maintenance Optimization for Aviation Technical Support Systems. Processes, 13(3), 666. https://doi.org/10.3390/pr13030666

Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., Siegel, D. 2014. Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications. Mechanical Systems and Signal Processing, 42(1–2), 314–334. https://doi.org/10.1016/j.

ymssp.2013.06.004
McKinsey & Company. 2020. Predictive maintenance 4.0: Beyond the hype. Industry report.
Meissner, R., Rahn, A., Wicke, K. 2021. Developing prescriptive maintenance strategies in the aviation industry based on a discrete-event simulation framework for post-prognostics decision making. Reliability Engineering & System Safety, 214, 107812. https://doi.org/10.1016/j.ress.2021.107812
Mobley, R. K. 2002. An Introduction to Predictive Maintenance (2nd ed.). Butterworth-Heinemann.
Muneer, A., Taib, S. M., Fati, S. M., Alhussian, H. 2021. Deep-Learning Based Prognosis Approach for Remaining Useful Life Prediction of Turbofan Engine. Symmetry, 13(10), 1861. https://doi.org/10.3390/sym13101861
NTSB. 2023. Aviation accident database query: Helicopter maintenance-related incidents (1982-2024). URL: https://www.ntsb.gov/Pages/ResultsV2.aspx?queryId=fb47651f-4fb1-4c22-a680-89c372373a1a (date of access: 07.03.2025)
Saxena, A., Celaya, J., Balaban, E., Goebel, K., Saha, B., Saha, S., Schwabacher, M. 2008. Metrics for evaluating performance of prognostic techniques. 2008 International Conference on Prognostics and Health Management, 1—17. https://doi.org/10.1109/PHM.2008.4711436
Si, X. S., Wang, W., Hu, C. H., Zhou, D. H. 2011. Remaining useful life estimation—A review. IEEE Transactions on Reliability, 60(2), 476—493. https://doi.org/10.1109/TR.2011.2138700
Smith, J. D., Johnson, R. L. 2018. Aviation Safety and Risk Management. Routledge.
Tsui, K. L., Chen, N., Zhou, Q., Hai, Y., Wang, W. 2015. Prognostics and health management: A review on data-driven approaches. Mathematical Problems in Engineering, 2015, 793161. https://doi.org/10.1155/2015/793161
Vachtsevanos, G., Lewis, F. L., Roemer, M., Hess, A., Wu, B. 2006. Intelligent Fault Diagnosis and Prognosis for Engineering Systems. John Wiley & Sons.
Wang, P., Youn, B. D. 2019. A generic probabilistic framework for structural health monitoring and prognosis of various engineering systems. Structural Health Monitoring, 18(3), 910—928. https://doi.org/10.1177/1475921718765943
Willis Towers Watson. 2023. General Aviation Insurance Market Review Q3 2023. https://www.wtwco.com/en-gb/insights/2023/09/general-aviation-insurance-market-review-q3-2023

СПИСОК ИСТОЧНИКОВ

Airbus Helicopters. 2021. Health and Usage Monitoring Systems (HUMS) Overview. Airbus Technical White Paper.
Allianz Commercial. 2023. Aviation Risk 2023: Aviation risk, claims and insurance outlook.
AS350 Maintenance Manual. 2023. Airbus Helicopters.
Bell Textron. 2022. Integrated Vehicle Health Monitoring Systems. Bell Technical Report.
Boeing. (2020). Aircraft Health Management: Implementation Guide. Boeing Technical Report.
Cokorilo, O., Gvozdenovic, S., Vasov, L., Mirosavljevic, P. 2010. Costs of unsafety in aviation. Technological and Economic Development of Economy, 16(1), 188—201. https://doi.org/10.3846/tede.2010.12
EASA. 2022. DATAPP (Digital Transformation — Case Studies for Aviation Safety Standards — Data Science Applications). https://www.easa.europa.eu/en/research-projects/datapp-digital-transformation-case-studies-aviation-safety-standards-data-science
Eurocopter. 2019. Vibration Health Monitoring System Manual. Eurocopter.
FAA. 2021. Advisory Circular AC 29-2C: Continued Operational Safety for Rotorcraft. Federal Aviation Administration.
Heng, A., Zhang, S., Tan, A. C. C., Mathew, J. 2009. Rotating machinery prognostics: State of the art. Mechanical Systems and Signal Processing, 23(3), 724—739. https://doi.org/10.1016/j.ymssp.2008.06.009
Hunemohr, D., Litzba, J., Rahimi, F. 2022. Usage Monitoring of Helicopter Gearboxes with ADS-B Flight Data. Aerospace, 9(11), 647. https://doi.org/10.3390/aerospace9110647
IATA. 2022. Safety Report 2022: Incorporating Maintenance and Operational Data. IATA

Publications.
ICAO. 2019. Operational (OPS) Safety Risks, Global Aviation Safety Plan. Retrieved from https://www.icao.int/GASP/operational-ops-safety-risks
ICAO. 2020. Manual of Aircraft Maintenance Management (Doc 9760).
Ivanov D.D., Frolov K.V. 2023. Optimizing the process of defining areas of responsibility in the context of small aircraft leasing using EAM systems. Technoeconomics 2, 3 (6), 4-15.
Иванов Д.Д., Фролов К.В., Дубгорн А.С. 2024. Организация интегрированной логистической поддержки в условиях арктической авиации. Авиакосмическое приборостроение 3, 53-64.
Иванов Д.Д., Фролов К.В., Левина А.И. 2024. Построение концептуального описания имитационной модели эксплуатации воздушных судов в рамках задачи классификации пунктов наземного обслуживания. Авиакосмическое приборостроение 1, 55-68.
ISO. 2019. ISO 13374-1:2019. Condition monitoring and diagnostics of machines — Data processing, communication and presentation. International Organization for Standardization.
Jardine, A. K. S., Lin, D., Banjevic, D. 2006. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing, 20(7), 1483–1510. https://doi.org/10.1016/j.ymssp.2005.09.012
Kabashkin, I., Perekrestov, V., Pivovar, M. 2025. AI-Driven Fault Detection and Maintenance Optimization for Aviation Technical Support Systems. Processes, 13(3), 666. https://doi.org/10.3390/pr13030666
Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., Siegel, D. 2014. Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications. Mechanical Systems and Signal Processing, 42(1–2), 314–334. https://doi.org/10.1016/j.ymssp.2013.06.004
McKinsey & Company. 2020. Predictive maintenance 4.0: Beyond the hype. Industry report.
Meissner, R., Rahn, A., Wicke, K. 2021. Developing prescriptive maintenance strategies in the aviation industry based on a discrete-event simulation framework for post-prognostics decision making. Reliability Engineering & System Safety, 214, 107812. https://doi.org/10.1016/j.ress.2021.107812
Mobley, R. K. 2002. An Introduction to Predictive Maintenance (2nd ed.). Butterworth-Heinemann.
Muneer, A., Taib, S. M., Fati, S. M., Alhussian, H. 2021. Deep-Learning Based Prognosis Approach for Remaining Useful Life Prediction of Turbofan Engine. Symmetry, 13(10), 1861. https://doi.org/10.3390/sym13101861
NTSB. 2023. Aviation accident database query: Helicopter maintenance-related incidents (1982-2024). URL: https://www.ntsb.gov/Pages/ResultsV2.aspx?queryId=fb47651f-4fb1-4c22-a680-89c372373a1a (date of access: 07.03.2025)
Saxena, A., Celaya, J., Balaban, E., Goebel, K., Saha, B., Saha, S., Schwabacher, M. 2008. Metrics for evaluating performance of prognostic techniques. 2008 International Conference on Prognostics and Health Management, 1–17. https://doi.org/10.1109/PHM.2008.4711436
Si, X. S., Wang, W., Hu, C. H., Zhou, D. H. 2011. Remaining useful life estimation—A review. IEEE Transactions on Reliability, 60(2), 476–493. https://doi.org/10.1109/TR.2011.2138700
Smith, J. D., Johnson, R. L. 2018. Aviation Safety and Risk Management. Routledge.
Tsui, K. L., Chen, N., Zhou, Q., Hai, Y., Wang, W. 2015. Prognostics and health management: A review on data-driven approaches. Mathematical Problems in Engineering, 2015, 793161. https://doi.org/10.1155/2015/793161
Vachtsevanos, G., Lewis, F. L., Roemer, M., Hess, A., Wu, B. 2006. Intelligent Fault Diagnosis and Prognosis for Engineering Systems. John Wiley & Sons.
Wang, P., Youn, B. D. 2019. A generic probabilistic framework for structural health monitoring and prognosis of various engineering systems. Structural Health Monitoring, 18(3), 910–928. https://doi.org/10.1177/1475921718765943
Willis Towers Watson. 2023. General Aviation Insurance Market Review Q3 2023. https://www.wtwco.com/en-gb/insights/2023/09/general-aviation-insurance-market-review-q3-2023

INFORMATION ABOUT AUTHOR / ИНФОРМАЦИЯ ОБ АВТОРЕ

GUMBO Kudakwashe – student.
E-mail: gumbokudakwashe1999@gmail.com
ГУМБО Кудакваше – студент.
E-mail: gumbokudakwashe1999@gmail.com

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INTEGRATING INDUSTRY 5.0 TECHNOLOGIES INTO ENTERPRISE SYSTEMS: A SUSTAINABILITY APPROACH FOR NESTE

Mohammed Abdullah Hayel Al-sharabi ✉

Sana'a University, Sana'a, Yemen

✉ mahalsharabi@gmail.com

Abstract. This case study explores the integration of Industry 5.0 technologies — Artificial Intelligence (AI), Internet of Things (IoT), and Blockchain—into the enterprise systems of Neste, a global leader in renewable fuels and circular economy solutions. The study examines how these technologies can enhance operational sustainability and support Environmental, Social, and Governance (ESG) goals by addressing specific gaps in the company's digital infrastructure. Through a layered enterprise architecture analysis, the paper identifies opportunities for improving predictive capabilities, real-time monitoring, and ESG transparency. A three-phase roadmap is proposed to guide Neste's transition toward a more human-centric and sustainable digital operating model. The study contributes to the literature by offering a practical, standards-aligned framework that supports long-term value creation and ESG compliance through technological innovation.

Keywords: industry 5.0, sustainability, environmental social governance, artificial intelligence, internet of things, blockchain, enterprise architecture, digital transformation

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ИНТЕГРАЦИЯ ТЕХНОЛОГИЙ ИНДУСТРИИ 5.0 В КОРПОРАТИВНЫЕ СИСТЕМЫ: ПОДХОД К УСТОЙЧИВОМУ РАЗВИТИЮ ДЛЯ КОМПАНИИ NESTE

Мохаммед Абдулла Хайель Аль-Шараби ✉
Университет Саны, Санаа, Йемен
✉ mahalsharabi@gmail.com

Аннотация. В данном исследовании рассматривается интеграция технологий Индустрии 5.0 — искусственного интеллекта (ИИ), Интернета вещей (IoT) и блокчейна — в корпоративные системы компании Neste, мирового лидера в области возобновляемых видов топлива и решений для экономики замкнутого цикла. Исследование анализирует, как эти технологии могут повысить операционную устойчивость и поддержать цели в области экологии, социальной ответственности и корпоративного управления (ESG) путем устранения конкретных пробелов в цифровой инфраструктуре компании. С помощью многоуровневого анализа корпоративной архитектуры в работе определены возможности для улучшения прогнозных возможностей, мониторинга в реальном времени и прозрачности в вопросах ESG. Предлагается трехэтапная дорожная карта для перехода Neste к более человекоцентричной и устойчивой цифровой операционной модели. Исследование вносит вклад в литературу, предлагая практическую, соответствующую стандартам структуру, которая поддерживает создание долгосрочной ценности и соблюдение требований ESG посредством технологических инноваций.

Ключевые слова: индустрия 5.0, устойчивое развитие, экологическое социальное управление, искусственный интеллект, интернет вещей, блокчейн, корпоративная архитектура, цифровая трансформация

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Introduction

The transition from Industry 4.0 to Industry 5.0 marks a significant evolution in how digital technologies are applied within enterprises. While Industry 4.0 emphasized automation, interconnectivity, and operational efficiency, Industry 5.0 promotes a human-centric, sustainable, and resilient approach to value creation. This paradigm shift is particularly relevant as firms face increasing pressure from regulators, investors, and society to meet environmental, social, and governance (ESG) goals while maintaining competitiveness.

In parallel, enterprise systems—such as Enterprise Asset Management (EAM), Supply Chain Management (SCM), and Enterprise Resource Planning (ERP)—are becoming critical platforms for embedding sustainability objectives. However, many of these systems remain fragmented, reactive, and limited in their ability to support real-time ESG performance monitoring or compliance with circular economy principles.

Neste, a Finland-based global leader in renewable fuels and circular solutions, offers a relevant context to explore how emerging technologies associated with Industry 5.0—namely Artificial Intelligence (AI), the Internet of Things (IoT), and Blockchain—can be strategically integrated into enterprise systems to enhance sustainability outcomes. Despite the company's commitment to carbon-neutral production by 2035, it continues to face challenges in predictive maintenance, real-time emissions monitoring, and traceability in ESG reporting.

This study addresses the following research question:

How can AI, IoT, and Blockchain be integrated into enterprise systems to improve ESG performance and sustainability outcomes in industrial organizations?

To investigate this, we adopt a qualitative case study approach grounded in enterprise architecture analysis. Through the case of Neste, the study identifies key technological and functional gaps, maps relevant technologies to ESG objectives, and develops a layered integration framework supported by a phased implementation roadmap.

The study contributes to the information systems field by offering a replicable digital transformation model that aligns with Industry 5.0 principles and ESG frameworks.

It should be noted that the proposed framework is conceptual and derived from publicly available data and secondary sources. While this approach enables a structured analysis, it does not capture all operational constraints faced during real-world implementation. Therefore, the quantitative impacts discussed should be interpreted as indicative rather than deterministic.

Materials and Methods

This research adopts a qualitative case study methodology to explore the integration of Industry 5.0 technologies into enterprise systems for enhancing sustainability performance. The case study approach is appropriate for examining contemporary phenomena within real-world contexts, especially when boundaries between the phenomenon and context are not clearly defined (Yin, 2018). By focusing on a single, information-rich case, the study aims to generate deep, contextualized insights into how Artificial Intelligence (AI), the Internet of Things (IoT), and Blockchain can be embedded within enterprise architecture to support Environmental, Social, and Governance (ESG) goals.

Case Selection

Neste was selected as the focal case due to its recognized leadership in renewable fuels and circular economy innovation. As a company that has publicly committed to achieving carbon-neutral production by 2035 and reducing customer greenhouse gas emissions by 20 million tons annually by 2030, Neste presents a compelling setting for studying the alignment of sustainability strategy with digital transformation initiatives (Neste, 2023). Its complex industrial operations and advanced digital infrastructure also provide a suitable testbed for investigating how Industry 5.0 technologies can be operationalized.

Data Sources

The analysis draws upon multiple secondary data sources to ensure triangulation and enhance validity. These include:

— Publicly available corporate sustainability and digital transformation reports (e.g., Neste's Annual Sustainability Reports)

— Industry white papers and digital benchmarks

— International standards such as ISO 9001 (Quality Management Systems), ISO 14001 (Environmental Management Systems), and ISO 50001 (Energy Management Systems)

— ESG disclosure frameworks including the Global Reporting Initiative (GRI), Sustainability Accounting Standards Board (SASB), and Task Force on Climate-related Financial Disclosures (TCFD) (GRI, 2021; SASB, 2020)

— Academic and practitioner literature on AI, IoT, and Blockchain integration in enterprise systems (e.g., Muller et al., 2021; Wang et al., 2020)

Analytical Framework

The research follows a three-step analytical framework aligned with enterprise architecture modeling principles (TOGAF, 2018), consisting of:

1. Enterprise Systems Assessment

Evaluation of Neste's existing enterprise systems—Enterprise Asset Management (EAM), Supply Chain Management (SCM), and Enterprise Resource Planning (ERP)—to identify architectural and functional gaps hindering ESG performance.

2. Technology-to-ESG Mapping

Mapping the capabilities of AI, IoT, and Blockchain technologies to specific sustainability indicators and process deficiencies. This includes identifying how these technologies contribute to improving resource efficiency, emissions tracking, and transparency.

3. Framework and Roadmap Development

Designing a multi-layered integration framework (business, application, and technology layers) and a phased roadmap to support scalable, standards-aligned digital transformation aligned with ESG targets.

Results and Discussion

Enterprise System Assessment and Integration Opportunities

Enterprise Asset Management (EAM): Neste's EAM schedules and logs maintenance but remains largely time- or usage-based. It does not use sensor-driven analytics to predict failures or optimize energy use. We identified key gaps: no predictive analytics, no real-time monitoring of heavy machinery, and limited emissions optimization during maintenance. These issues mirror broader industry patterns: without AI-driven insights, maintenance tends to be reactive, causing unplanned downtime and waste. For example, case studies show that AI-based predictive maintenance on sensor data can forecast equipment health and cut downtime significantly (Marti-Puig et al., 2024; Ignatiev and Levina, 2024). IoT sensors (vibration, temperature, etc.) can continuously feed health and energy data, enabling condition-based scheduling in line with ISO 50001 principles. In practice, linking sensors to an AI engine has been shown to detect faults early and eliminate some outages (Uhlmann, Polte & Geisert, 2024). This transition from "run-to-failure" to condition-based maintenance can reduce resource waste and energy use.

Supply Chain Management (SCM): Neste's SCM handles procurement, inventory and logistics, but only tracks materials in batches after the fact. It lacks live visibility of shipments, and sustainability credentials are checked manually. We found no IoT tracking of renewable feedstocks, weak ESG data from suppliers, and slow audit processes for certifications. Industry solutions exist: GPS trackers and environmental sensors on containers can stream location and condition data in real time, greatly improving logistics efficiency. Studies on blockchain in IIoT context show that combining IoT and blockchain creates an immutable, real-time ledger of supply flows (Soori et al., 2024). For example, IoT sensors can monitor transport conditions, while blockchain records each supply chain event securely. This combination enables end-to-end traceability of raw materials and fuels. AI also enhances SCM: by analyzing traffic and weather data, AI can optimize routing to cut fuel consumption (a model shown to reduce transport energy use by ~10%). Blockchain's immutable chain then verifies that feedstocks are sustainably sourced, automating audits and building trust (Shen ,Cui ,Chen ,Huang & Sarker S, 2025). Enterprise Resource Planning (ERP): Neste's ERP integrates finance and some ops with nascent sustainability reporting. However, sustainability data largely lives in silos – one team's spreadsheets are another's. Real-time dashboards for emissions or resource use are absent, and reporting is manual with low auditability. This impairs transparency and response time. AI analytics can remedy this by unifying data streams (from IoT sensors, maintenance logs, supply records) to automatically flag ESG KPIs out of range (Ayvaz & Alpay, 2021). For example, an AI engine could detect a spike in energy use or a deviation in GHG intensity and alert managers instantly. Blockchain adds integrity: by recording emissions data and carbon credit transactions in a tamper-proof ledger, it prevents post-hoc manipulation. Prior work in industrial informatics suggests blockchain can secure ESG disclosures: sensor data feeding directly into blockchain eliminates "garbage in, garbage out" errors and ensures traceable audit trails (Shen et al.,2025; Martini, Bellisario, & Coletti, 2024).

Integration Framework and Roadmap

To implement these solutions, we propose a layered integration framework (aligned with TOGAF). The Business layer embeds ESG and circular economy goals into corporate strategy. Sustainability KPIs (e.g., ISO 14001, ISO 50001 targets) are linked to digital initiatives so that technology projects explicitly support those goals. The Application layer integrates AI modules into EAM and SCM and advanced analytics into ERP. For instance, an AI analytics service can push maintenance forecasts into EAM, supply-demand forecasts into SCM, and ESG alerts into ERP. The Technology layer deploys IoT networks and blockchain infrastructure: IoT devices across plants and logistics capture live data, while blockchain nodes store traceability and audit records. This architecture ensures seamless, ESG-aligned data flows. AI engines consume sensor data to drive EAM and SCM decisions (Marti-Puig et al., 2024). IoT feeds live production and transport data into SCM/EAM and into a unified data lake for ERP analysis. Blockchain interfaces with ERP/SCM to register transactions and trigger smart contracts for compliance checks (Shen et al., 2025).

Implementation Roadmap:

We outline a phased deployment. In Phase 1 (0–6 months), pilot programs validate core use cases with minimal disruption. For example, trials might deploy AI predictive maintenance on one plant's critical assets, install IoT sensors on key emissions sources, and set up a blockchain proof-of-concept for one supply chain stream. These pilots generate initial ROI and technical lessons. In Phase 2 (6–18 months), successful pilots are scaled: AI tools expand into SCM demand forecasting and emissions modeling; IoT sensors cover all major equipment and vehicles; blockchain is rolled into the ERP for carbon accounting and sustainability reports. By Phase 2 end, ESG dashboards become live across core operations. Phase 3 (18–36 months) focuses on optimization and expansion: aggregated AI/IoT insights automate workflows and energy balancing; smart contracts fully automate compliance and audits; the system is extended to new business units and global sites. Throughout, progress is tracked by milestones: e.g., initial pilots achieve $\geq$10% downtime reduction, Phase 2 reaches ~70% system coverage, and Phase 3 realizes $\geq$50% faster ESG reporting.

Table 1. Integration of Industry 5.0 Technologies and ESG Improvements.

System	Identified Gap	Technology Applied	ESG Improvement	Impact
EAM (Enterprise Asset Management)	Reactive, time-based maintenance; energy inefficiency	AI + IoT (predictive maintenance, real-time monitoring)	Reduced resource waste and energy use	~20% reduction in downtime; ~15% less maintenance energy use
SCM (Supply Chain Management)	Lack of real-time visibility; inefficient routing; fragmented supplier data	IoT + AI (live tracking, predictive logistics); Blockchain (traceability ledger)	Optimized transport; verified sustainable sourcing	~10% drop in transport fuel; 100% traceability; 50% faster audits
ERP (Enterprise Resource Planning)	Siloed ESG data; manual reporting; risk of tampering	AI (ESG analytics); Blockchain (secure recordkeeping)	Transparent ESG dashboards; tamper-proof compliance	Reporting time cut by 50%; 0 discrepancies in audits

Impact Analysis: discrepancies in audits The proposed integration is expected to significantly boost ESG performance along three dimensions.

Resource Efficiency: AI-driven predictive maintenance and IoT monitoring directly improve resource use. By moving from scheduled to condition-based maintenance, machines run more reliably. The literature indicates such AI systems can substantially reduce downtime and energy waste (Marti-Puig et al., 2024). IoT sensors continuously measure energy and material flows at the factory, making inefficiencies immediately visible. For instance, live energy dashboards enable teams to spot and fix leaks or machine idling. Blockchain contributes by streamlining verification of sustainable practices (e.g., renewable materials usage) and reducing audit labor. KPIs reflect these gains: unplanned downtime can fall by ~20%, and maintenance energy use by ~15% (Marti-Puig et al., 2024)., meaning more production for the same inputs.

Emissions Reduction: AI models can predict emissions from various production scenarios. By simulating process changes or startup sequences, the system suggests low-carbon operating modes proactively. Real-time IoT sensors (e.g., CO_2 or NOx detectors on chimneys) then alert operators to anomalies. Quick interventions reduce spikes and overall emissions. A blockchain ledger ensures all emissions data are recorded immutably, simplifying regulatory audits. Blockchain-based carbon credit platforms, as Soori et al report, can cut audit time and costs (Soori et al., 2024). This combined approach can yield substantial CO_2 cuts; for example, pilot zones may see 10–30% lower emissions under AI/IoT control. Response cycles also shorten, as issues are detected in near real time.

Transparency in ESG Reporting: By funneling sensor and operational data into ERP, AI-enabled platforms can generate ESG reports automatically. This reduces manual entry errors and slashes reporting time. We anticipate up to a 50% reduction in report preparation based on analogous automation projects. Blockchain seals the trust: immutable ledgers and smart contracts guarantee that once data (e.g., energy usage, carbon output) is logged, it cannot be altered. This fortifies compliance with GRI/SASB frameworks. In the supply chain, blockchain ensures end-to-end traceability of renewable inputs: every batch's origin is recorded. The result is 100% provenance of critical materials, enhancing stakeholder trust. Documented blockchain pilots in consumer goods supply chains, including Unilever's traceability initiatives, suggest that blockchain-based systems can enhance the credibility of sustainability claims by strengthening data provenance and auditability (Shen et al., 2025). In a similar manner, the combined integration of AI, IoT, and blockchain within enterprise systems has the potential to support more transparent and data-driven ESG governance at Neste. By improving the monitoring of resource use and greenhouse gas emissions, such an approach is expected to contribute to the company's carbon-neutral production objectives. More reliable and timely disclosures may also strengthen stakeholder confidence by reducing information asymmetry and post hoc data manipulation.

Strategic Integration and Change Management

Effective implementation requires a coherent integration strategy. We advocate a modular, API-driven architecture so that innew AI/IoT components plug into existing EAM/SCM/ERP systems. For example, AI analytic services process maintenance history and sensor streams to output maintenance schedules into EAM (Marti-Puig et al., 2024). IoT data feeds seamlessly into SCM for inventory tracking and into EAM for machine health. Blockchain nodes are connected to ERP/SCM to store transactions and to smart contracts that automate supplier ESG verifications (Shen et al., 2025). Edge computing handles time-critical sensor data on-site, while cloud/central servers perform batch analytics. Smart contracts automatically check supplier certificates, emissions thresholds, or carbon credit rules without manual intervention.

Change Management: Technology is only half the story. Staff must be trained on these new systems – from interpreting IoT dashboards to understanding AI-generated maintenance alerts and blockchain records. Stakeholders (sustainability officers, IT, operations) should guide the process from the start to align digital goals with business needs. We recommend an iterative rollout: begin with pilots to demonstrate value, gather feedback, then expand. Communication is key to overcome resistance: show how these tools reduce drudgery (less manual reporting) and improve outcomes.

Risk Mitigation: Key risks include resistance to change, integration complexity, and cybersecurity. We mitigate these by using modular design and middleware for interoperability, setting up a cross-functional steering committee for approach itself allows early identification and correction of issues.

Conclusion

This case study shows that AI, IoT, and blockchain can be woven into enterprise systems to drive sustainability. By transforming EAM, SCM, and ERP from siloed tools into a predictive, transparent platform, Neste can meet its ESG goals more effectively. Specifically, we found that embedding AI enables proactive maintenance and emissions management; IoT provides the real-time data backbone for efficiency; and blockchain guarantees data integrity and traceability of ESG information (Khan et al., 2025; Rame, Purwanto & Sudarno, 2024). The proposed integration framework and roadmap answer our research question: they illustrate how these technologies work together to improve ESG performance, with clear examples (e.g., reduced downtime, fuel savings, audit acceleration).

Managers can use this model as practical guidance: start small with pilots, align each tech deployment with specific sustainability KPIs, and expand as gains are realized. For researchers, the study offers a structured link between Industry 5.0 concepts and enterprise architecture, suggesting many future questions (e.g., cross-industry validation, economic impact analysis). As Industry 5.0 grows, our findings imply that success lies in blending technology with human-centric sustainability governance.

REFERENCES

Ayvaz S., Alpay K. 2021. Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time. Expert Systems with Applications 173, 114598. DOI:10.1016/j.eswa.2021.114598.

Ignatiev P., Levina A. 2024. Artificial intelligence and artificial neural networks in healthcare. Technoeconomics 3, 4 (11), 28–41. DOI: https://doi.org/10.57809/2024.3.4.11.3

International Organization for Standardization. ISO 9001: Quality management systems – Requirements. Geneva: ISO; 2015.

International Organization for Standardization. ISO 14001: Environmental management systems – Requirements with guidance for use. Geneva: ISO; 2015.

International Organization for Standardization. ISO 50001: Energy management systems – Requirements with guidance for use. Geneva: ISO; 2018.

Khan M.I., Yasmeen T., Khan M., Hadi N.U., Asif M., Farooq M., Al-Ghamdi S.G. 2025. Integrating Industry 4.0 for enhanced sustainability: Pathways and prospects. Sustainable Production and Consumption 54, 149–189. DOI:10.1016/j.spc.2024.12.012.

Lee J., Bagheri B., Kao H.A. 2015. A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. Manufacturing Letters 3, 18–23. DOI:10.1016/j.mfglet.2014.12.001.

Marti-Puig P., Touhami I.A., Colomer Perarnau R., Serra-Serra M. 2024. Industrial AI in condition-based maintenance: A case study in wooden piece manufacturing. Computers & Industrial Engineering 188, 109907. DOI:10.1016/j.cie.2024.109907.

Martini B., Bellisario D., Coletti P. 2024. Human-centered and sustainable artificial intelligence in Industry 5.0: Challenges and perspectives. Sustainability 16(13), 5448. DOI:10.3390/su16135448.

Neste Sustainability Report 2023 [Electronic at: https://www.neste.com (accessed: 01.04.2025).

Neste Green Finance Report 2023 [Electronic at: https://www.neste.com/files/pdf/2C-2QgEprNYVxlOgq4zfVAN Neste_Green_Finance_Report_2023.pdf (accessed: 01.04.2025). resource]. 2023. resource]. 2023. Available Available

Neste Sustainability [Electronic resource]. Available at: https://www.neste.com/en us/sustainability (accessed: 01.04.2025).

Rame R., Purwanto, S. 2024. Industry 5.0 and sustainability: An overview of emerging trends and challenges for a green future. Innovation and Green Development 3(4), 100173. DOI:10.1016/j.igd.2024.100173.

Reporting Initiative. GRI Standards [Electronic resource]. 2021. URL: https://www.globalreporting.org (accessed: 10.04.2025).

Saberi S., Kouhizadeh M., Sarkis J., Shen L. 2019. Blockchain technology and its relationships to sustainable supply chain management. International Journal of Production Research 57(7), 2117–2135. DOI:10.1080/00207543.2018.1533261.

Shen H., Cui L., Chen Y., Huang Z., Sarker S. 2025. Leveraging blockchain technology to prevent deceptive disclosure of ESG compliance. Transportation Research Part E: Logistics and Transportation Review 203, 104360.

Soori M., Karimi Ghaleh Jough F., Dastres R., Arezoo B. 2024. Blockchains for Industrial Internet of Things in sustainable supply chain management of Industry 4.0: A review. Sustainable Manufacturing and Service Economics 3, 100026. DOI:10.1016/j.smse.2024.100026.

Sustainability Accounting Standards Board. 2020. SASB Standards. URL: https://www.sasb.org (accessed: 10.04.2025).

The Open Group. 2018. The Open Group Architecture Framework (Version 9.2). Zaltbommel: Van Haren Publishing.

Uhlmann E., Polte J., Geisert C. 2025. IoT-based energy monitoring in production. Measurement: Sensors 38(Suppl), 101591. DOI:10.1016/j.measen.2024.101591.

Wamba S.F., Gunasekaran A., Akter S., Ren S.J., Dubey R., Childe S.J. 2017. Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research 70, 356-365. https://doi.org/10.1016/j.jbusres.2016.08.009

Wang Y., Han J., Beynon-Davies P. 2020. Understanding blockchain technology for future supply chains: A systematic literature review and research agenda. Supply Chain Management: An International Journal 25(6), 729–748. DOI:10.1108/SCM-03-2018-0148.

Yin R.K. 2017. Case Study Research and Applications: Design and Methods. 6th ed. Thousand Oaks: Sage Publications.

СПИСОК ИСТОЧНИКОВ

Ayvaz S., Alpay K. 2021. Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time. Expert Systems with Applications 173, 114598. DOI:10.1016/j.eswa.2021.114598.

Ignatiev P., Levina A. 2024. Artificial intelligence and artificial neural networks in healthcare. Technoeconomics 3, 4 (11), 28–41. DOI: https://doi.org/10.57809/2024.3.4.11.3

International Organization for Standardization. ISO 9001: Quality management systems – Requirements. Geneva: ISO; 2015.

International Organization for Standardization. ISO 14001: Environmental management systems – Requirements with guidance for use. Geneva: ISO; 2015.

International Organization for Standardization. ISO 50001: Energy management systems – Requirements with guidance for use. Geneva: ISO; 2018.

Khan M.I., Yasmeen T., Khan M., Hadi N.U., Asif M., Farooq M., Al-Ghamdi S.G. 2025. Integrating Industry 4.0 for enhanced sustainability: Pathways and prospects. Sustainable Production and Consumption 54, 149–189. DOI:10.1016/j.spc.2024.12.012.

Lee J., Bagheri B., Kao H.A. 2015. A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. Manufacturing Letters 3, 18–23. DOI:10.1016/j.mfglet.2014.12.001.

Marti-Puig P., Touhami I.A., Colomer Perarnau R., Serra-Serra M. 2024. Industrial AI in condition-based maintenance: A case study in wooden piece manufacturing. Computers & Industrial Engineering 188, 109907. DOI:10.1016/j.cie.2024.109907.

Martini B., Bellisario D., Coletti P. 2024. Human-centered and sustainable artificial intelligence in Industry 5.0: Challenges and perspectives. Sustainability 16(13), 5448. DOI:10.3390/su16135448.

Neste Sustainability Report 2023 [Electronic at: https://www.neste.com (accessed: 01.04.2025).

Neste Green Finance Report 2023 [Electronic at: https://www.neste.com/files/pdf/2C-2QgEprNYVxlOgq4zfVAN Neste_Green_Finance_Report_2023.pdf (accessed: 01.04.2025). resource]. 2023. resource]. 2023. Available Available

Neste Sustainability [Electronic resource]. Available at: https://www.neste.com/en us/sustainability (accessed: 01.04.2025).

Rame R., Purwanto, S. 2024. Industry 5.0 and sustainability: An overview of emerging trends and challenges for a green future. Innovation and Green Development 3(4), 100173. DOI:10.1016/j.igd.2024.100173.

Reporting Initiative. GRI Standards [Electronic resource]. 2021. URL: https://www.globalreporting.org (accessed: 10.04.2025).

Saberi S., Kouhizadeh M., Sarkis J., Shen L. 2019. Blockchain technology and its relationships to sustainable supply chain management. International Journal of Production Research 57(7), 2117–2135. DOI:10.1080/00207543.2018.1533261.

Shen H., Cui L., Chen Y., Huang Z., Sarker S. 2025. Leveraging blockchain technology to prevent deceptive disclosure of ESG compliance. Transportation Research Part E: Logistics and Transportation Review 203, 104360.

Soori M., Karimi Ghaleh Jough F., Dastres R., Arezoo B. 2024. Blockchains for Industrial Internet of Things in sustainable supply chain management of Industry 4.0: A review. Sustainable Manufacturing and Service Economics 3, 100026. DOI:10.1016/j.smse.2024.100026.

Sustainability Accounting Standards Board. 2020. SASB Standards. URL: https://www.sasb.org (accessed: 10.04.2025).

The Open Group. 2018. The Open Group Architecture Framework (Version 9.2). Zaltbommel: Van Haren Publishing.

Uhlmann E., Polte J., Geisert C. 2025. IoT-based energy monitoring in production. Measurement: Sensors 38(Suppl), 101591. DOI:10.1016/j.measen.2024.101591.

Wamba S.F., Gunasekaran A., Akter S., Ren S.J., Dubey R., Childe S.J. 2017. Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research 70, 356-365. https://doi.org/10.1016/j.jbusres.2016.08.009

Wang Y., Han J., Beynon-Davies P. 2020. Understanding blockchain technology for future supply chains: A systematic literature review and research agenda. Supply Chain Management: An International Journal 25(6), 729–748. DOI:10.1108/SCM-03-2018-0148.

Yin R.K. 2017. Case Study Research and Applications: Design and Methods. 6th ed. Thousand Oaks: Sage Publications.

INFORMATION ABOUT AUTHOR / ИНФОРМАЦИЯ ОБ АВТОРЕ

AL-SHARABI Mohammed Abdullah Hayel – student.
E-mail: mahalsharabi@gmail.com
АЛЬ-ШАРАБИ Мохаммед Абдулла Хайель – студент.
E-mail: mahalsharabi@gmail.com

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PROFIT-RISK OPTIMIZATION TASK FOR A HYBRID WAREHOUSE CONFIGURATION

Semen Ermochenko ✉

Peter the Great St. Petersburg Polytechnic University, St. Petersburg, Russia

✉ esemion10@gmail.com

Abstract. Object of study: hybrid warehouse architecture for e-commerce, integrating a physical warehouse and a virtual dropshipping channel. Methods: comparative analysis based on financial, operational, and risk-oriented indicators, supported by a mathematical framework incorporating supplier reliability. Results: the study reveals fundamental trade-offs between liquidity, risk, delivery speed, and costs. The hybrid model releases up to 40% of working capital but reduces profit by 25.3% at a supplier reliability of $\beta = 0.95$. Risk adjustment decreases expected profit by 11.25% compared to the nominal calculation. Conclusions: a verbal optimization problem is formulated to maximize profit under risk and delivery time constraints, providing a structured approach for managing hybrid systems instead of intuitive selection.

Keywords: hybrid warehouse architecture, inventory management, e-commerce, dropshipping, supplier reliability, risk management, profit optimization, supply chain, logistics, working capital, order fulfillment, multi-channel retail

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ЗАДАЧА ОПТИМИЗАЦИИ ПРИБЫЛИ И РИСКА ДЛЯ ГИБРИДНОЙ СКЛАДСКОЙ КОНФИГУРАЦИИ

Семён Ермоченко ✉

Санкт-Петербургский политехнический университет Петра Великого, Санкт-Петербург, Россия

✉ esemion10@gmail.com

Аннотация. Объект исследования — гибридная складская архитектура интернет-магазина, сочетающая физический склад и виртуальный канал по схеме дропшиппинга. Метод исследования включает сравнительный анализ архитектур на основе системы финансовых, операционных и риск-ориентированных показателей, а также разработку математического аппарата, учитывающего надежность поставщика. Результаты демонстрируют системные компромиссы между ликвидностью, риском, скоростью доставки и затратами: гибридная модель высвобождает оборотный капитал до 40%, но снижает прибыль на 25,3% при надежности поставщика β = 0,95. Учет риска снижает ожидаемую прибыль на 11,25% по сравнению с номинальным расчетом. Выводы: предложена вербальная постановка оптимизационной задачи максимизации прибыли при ограничениях на риск и время доставки, что позволяет перейти от интуитивного выбора к количественному управлению гибридной системой.

Ключевые слова: гибридная складская архитектура, управление запасами, электронная коммерция, дропшиппинг, надежность поставщика, управление рисками, оптимизация прибыли, цепь поставок, логистика, оборотный капитал, выполнение заказов, многоканальная торговля

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Introduction

In the modern world, the impact of digitalization on all sectors of the economy, including retail trade, is undeniable. The development of e-commerce has become not only a new sales channel but also a catalyst for significant changes in supply chain and logistics management. As Martin Christopher notes in his book "Logistics & Supply Chain Management," competition between individual companies is being replaced by competition between supply chains (Christopher, 2016). This trend exacerbates the problem of working capital management, as the need to maintain a high level of product availability for rapid customer delivery inevitably leads to the problem of "frozen" resources in inventory.

However, classical inventory management models, which underpin many systems, demonstrate low efficiency in the context of hybrid business models, whose architecture combines the operation of owned physical warehouses and online sales. Traditional push and pull strategies (Gou et al., 2016), prove insufficiently flexible in coordinating supply and demand in such models. This is because these strategies were developed for a context assuming unified control over logistics flows and full transparency of inventory information. In a hybrid environment, where some operations are outsourced to external suppliers (virtual warehouse), a fundamentally new risk architecture and cost structure emerge. The key challenge becomes not merely optimizing inventory levels, but optimally allocating products and demand between fundamentally different fulfillment channels, each characterized by a unique balance between operational costs, lead time, risks of default, and impact on cash flows.

Existing scientific works primarily focus either on traditional schemes with owned warehouses (Li and Mizuno, 2022; Soleimani et al., 2020; Xu et al., 2021; Babkina, 2024) or on models entirely based on outsourced capacities (Vandeput, 2020; Hasan et al., 2024). In the first case, researchers, following the classical paradigm, elaborate in detail on optimizing inventory management parameters (such as reorder point and safety stock levels) under stable or stochastic demand but ignore the possibility of dynamically redirecting orders to external capacities to reduce capital expenditures. In the second case, studying models like dropshipping, the emphasis shifts to supplier coordination and minimizing inventory investments; however, the strategic value of a combined approach, which allows for flexible distribution of product flows between channels based on their operational characteristics, is not considered. At the same time, combined approaches integrating both logics are not sufficiently studied. A review of contemporary research in inventory management for multi-channel retail confirms that, despite growing interest in the topic, research dedicated to the integration of physical and virtual warehouse accounting models remains limited, particularly in terms of determining optimal inventory allocation and risk-sharing mechanisms between channels (Ivanov et al., 2022; Kong et al., 2019). Modern research on digital warehouse management methods also confirms the complexity of integrating different logistics systems into a single circuit (Ishfaq and Raja, 2017). A vivid illustration of this limitation is modern research on hybrid systems, such as the work of Ishfaq and Raja, where order fulfillment options in retail supply chains are analyzed in detail. Despite the systematic approach to assessing operational trade-offs, the model considers the performance of external partners as a deterministic parameter. In practice, however, this parameter is a key source of uncertainty and requires its own forecasting and integration into the overall risk management system (Egorov et al., 2023; Wiedmer et al., 2021; Ivanov, 2020). Consequently, it can be argued that even in such advanced works, a fragmented approach persists: a specific optimization problem is solved without considering the full architecture of business processes and the dynamic nature of risks inherent in hybrid models.

Thus, the conducted literature analysis reveals a persistent research gap manifesting at three interconnected levels. At the conceptual level, there is a lack of a comprehensive approach to evaluating the effectiveness of a hybrid warehouse architecture as a unified system. At the methodological level, the mathematical framework capable of adequately accounting for the specific risks of virtual warehouses is underdeveloped. However, the application of business intelligence and digital systems in logistics shows potential for creating such integrated models (Iliasgenko et al., 2022). At the practical level, there are no formalized problem statements for optimization to find a balance between profit and risks.

The main purpose of this work is to develop a methodological approach to managing hybrid warehouse architecture, culminating in the formalization of the corresponding optimization task. To achieve this goal, the research solves the following tasks: a comparative analysis of the effectiveness of classical and hybrid models is carried out; a mathematical apparatus is being developed that integrates supplier reliability and risk assessment parameters; the impact of risk accounting on profit is demonstrated using a conditional example.; and, as a key result, a verbal formulation of an optimization problem is formulated, aimed at maximizing profits under given risk constraints and delivery time.

Materials and Methods

The object of this research comprises two architectures for an online store's inventory management system.

Architecture 1: Physical Warehouse Model. This model represents a classic system where the entire product assortment is stored in the company's owned physical warehouse. The order fulfillment process begins with a prepayment to the supplier, followed by the placement of goods in the owned warehouse. Subsequently, the customer places an online order and pays for it. A company employee locates the item in the warehouse, then packages it, prepares the necessary documentation, and hands over the ready order to a courier service for shipment. In this variant, all logistical operations and risks associated with storage and order fulfillment lie entirely with the company.

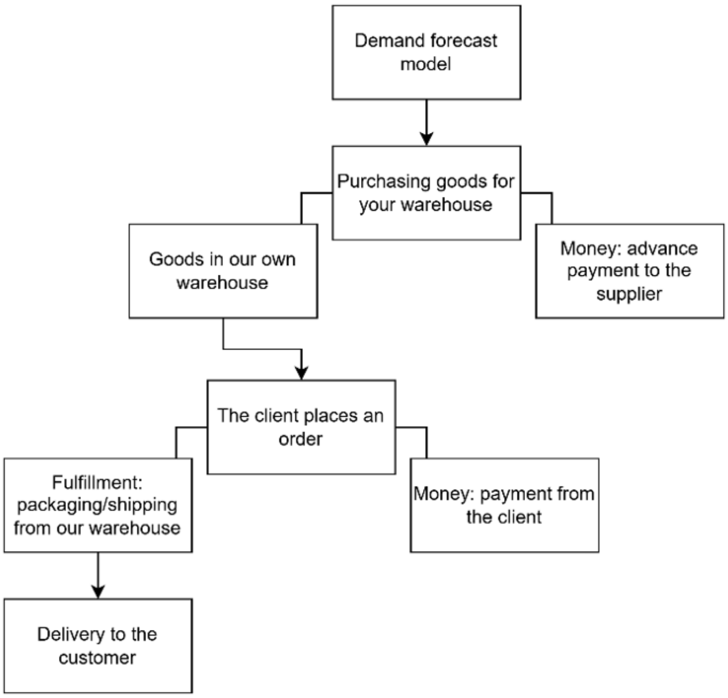

Fig. 1. Business process diagram of the classical inventory management model with a physical warehouse.

Architecture 2: Hybrid Model (Physical + Virtual Warehouse)

The second model involves the operation of an owned warehouse in conjunction with a virtual one. In this case, the virtual warehouse implies a dropshipping scheme. The key difference from the first model is that the company does not own the goods but uses the supplier's product catalog. The supplier, upon receiving an order, ships it directly to the customer from their own warehouse, while the company's warehouse is not involved. Such models, including dropshipping, require careful analysis of the strategic choice between different order fulfillment methods (Gelsomino et al., 2018; Wang et al., 2016).

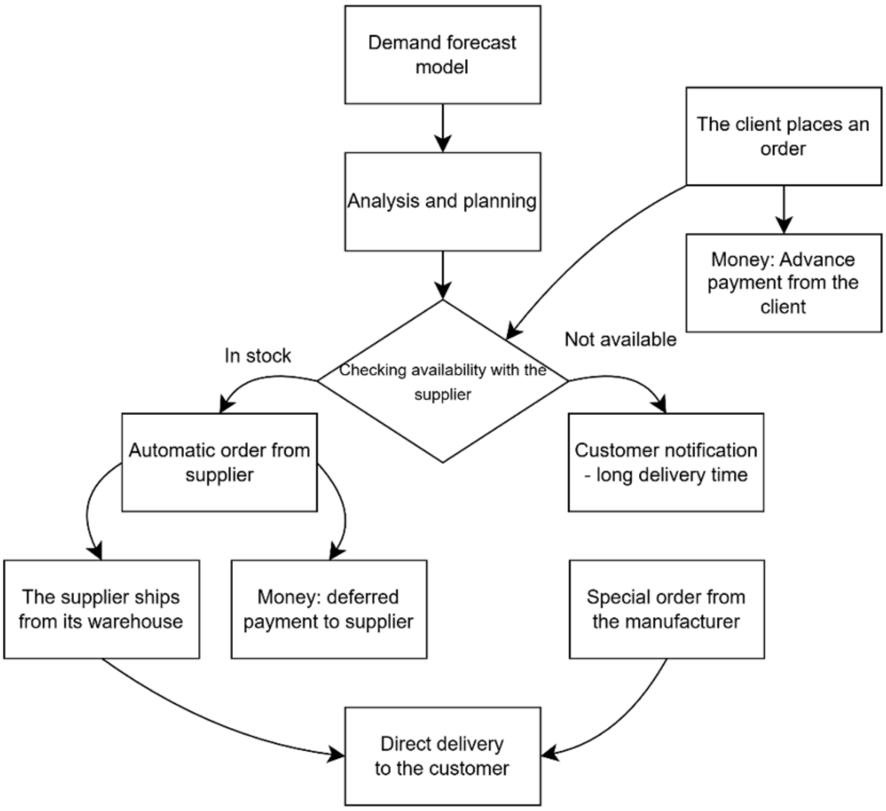

Fig. 2. Business process diagram of the hybrid inventory management model (physical warehouse + virtual warehouse).

To conduct a comparative analysis of the two architectures, a system of indicators was developed, covering key business aspects: financial efficiency, operational activities, and risk management. The choice of indicators is driven by the need to quantitatively assess the trade-offs arising from the integration of a virtual warehouse.

Cash Flow: Assesses the cash conversion cycle. Architecture 1 is characterized by a classic cycle with supplier prepayment. In Architecture 2, a negative conversion cycle arises, where payment from the customer is received before settlement with the supplier, thereby releasing working capital.

Customer Delivery Time: A key parameter of customer experience. For Architecture 1, delivery time is minimal and determined by logistics from the owned warehouse. For Architecture 2, delivery time increases by the supplier's order processing time and logistics from their warehouse, which is a variable.

Risk Structure: Qualitative and quantitative assessment of prevailing risk types. In Architecture 1, operational risks prevail: risks of deadstock and storage costs. In Architecture 2, operational risks are minimized, but partner risks emerge: risk of supplier unreliability (delays, defects) and risk of losing control over the process.

Profitability: Calculated using different formulas for the two models. For Architecture 1: Revenue − (Cost + Carrying Costs). For Architecture 2: Revenue − Supplier Price. The highlighted structure requires a separate calculation for accurate comparison.

Order Fulfillment Logistics Costs: In Architecture 1, costs include the formation of own logistics infrastructure and payroll. In Architecture 2, these costs are minimized and delegated to the supplier but are included in the higher purchase price.

Table 1. Comparative Analysis of Key Architectural Indicators.

Indicator	Architecture 1 (Physical Warehouse)	Architecture 2 (Hybrid Model)	Evaluation Method
Cash Flow	Classic cycle, prepayment to supplier first, then awaiting sale, funds "frozen" in inventory	Negative conversion cycle, payment from customer occurs before supplier settlement, working capital is released	Cash Conversion Cycle analysis
Delivery Time	Minimal, goods physically located at company warehouse, ready for shipment	Increased, variable, depends on supplier's processing speed	Statistical analysis of order fulfillment
Risk Structure	Operational risks: illiquid goods, storage, accounting, and logistics costs, inventory obsolescence	Partner risks: supplier unreliability, delays, defects, loss of process control	Qualitative assessment and quantitative evaluation of probability and cost of risk
Profitability	Revenue – (Cost + Storage Costs)	Revenue – Supplier Price	Calculation based on corresponding formulas using a unified initial data base
Fulfillment Costs	High, include formation of warehouse infrastructure and labor costs	Low/delegated, costs are included in the supplier's price	Analysis of operational cost structure

For the quantitative assessment of the comparative efficiency of the architectures and the subsequent formalization of the optimization problem, a mathematical framework was developed to account for the specific parameters of the hybrid model, primarily the risks associated with the reliability of the virtual warehouse supplier. The following main variables were introduced to formalize the model:

t – current time within the planning period T

$D(t)$ – forecasted demand for the product at time t, obtained from forecasting models

$S_{own}(t)$ – inventory level at the owned (physical) warehouse at time t

$S_{transit}(t)$ – volume of goods ordered from the virtual warehouse supplier and in transit (fulfillment status)

L_v – lead time of the virtual warehouse supplier (time from order placement to shipment to the customer)

β – supplier reliability parameter, probability of fulfilling an order within the agreed time L_v, where $0 \le \beta \le 1$.

R – risk cost estimate, financial losses from one failed delivery, including lost profit and penalties [Lost Profit + Penalties]

$P_{failure}$ – probability of delivery failure (1 – β)

C_{hold} – unit cost of holding one item in the owned warehouse

$Price_{sale}$ – selling price of the product to the end customer

$Cost_{own}$ – cost of goods in the owned warehouse (purchase price)

$Price_{supplier}$ – Product price from the virtual warehouse supplier

Based on the introduced parameters, key calculation formulas were defined:

Total available stock (including goods in transit):

$$S_{total}(t) = S_{own}(t) + S_{transit}(t)$$

Condition for placing a new order:

$$IF\ D(t) > S_{total}(t)\ THEN\ Q_{order} = D(t) - S_{total}(t)$$

where Q_{order} is the order volume.

Supplier risk assessment model:

$$E_{loss} = P_{failure} * R = (1-\beta) * [Lost\ Profit + Penalties]$$

Profit model for comparative analysis:

Architecture 1

$$Profit_1 = (Price_{sale} - Cost_{own} - C_{hold}) * Q_{sold}$$

where Q_{sold} – volume of goods sold

Architecture 2

$$Profit_2 = ((Price_{sale} - Price_{supplier}) * \beta - P_{failure} * R) * Q_{sold}$$

To demonstrate the application of the mathematical framework, an example with conditional initial data is considered. Let:

$Price_{sale}$ = 2000 rub.;

$Price_{supplier}$ = 1200 rub.;

β = 0.95;

R = 1000 rub., where *Lost Profit* = 800 rub., *Penalties* = 200 rub.;

Q_{sold} = 100 units;

Calculation for Architecture 1:

Profit ($Profit_1$): (2000 – 1000 – 50) * 100 = 950 * 100 = 95000 rub.

Calculation for Architecture 2:

Nominal profit (at β = 1): (2000 – 1200) * 100 = 80000 rub.

Expected losses: (1 – 0.95) * 1000 * 100 = 5000 rub.

Adjusted profit ($Profit_2$): 80000 * 0.95 – 5000 = 71000 rub.

The example clearly demonstrates that even with high supplier reliability (β = 0.95) accounting for risk reduces expected profit by 11.25% compared to the nominal calculation, confirming the necessity of using adjusted models for managerial decision-making. The developed mathematical apparatus makes it possible to quantify the comparative effectiveness of architectures using approaches similar to those used in modern research on hybrid supply chains (Li et al., 2022; Winkelmann and Spinler, 2022), as well as considering the evolution of digital systems in the economy through the adoption of multi-agent technologies (Antonov et al., 2025).

Results and Discussion

Based on the developed methodological approach and mathematical framework, results were obtained enabling a comprehensive comparative analysis of the two architectures and the formalization of the optimization problem as a verbal problem statement. Thanks to the practical example with conditional data, systemic differences between the two architectures can be identified. The key identified trade-offs include:

Liquidity vs. Risk Trade-off: The hybrid architecture demonstrates a significant (up to 40% in the considered example) release of working capital due to the negative cash conversion cycle. However, this advantage is offset by an increase in operational risks associated with supplier reliability. At β < 0.9, the aggregate risk of the hybrid model may exceed that of the classical architecture. This compromise is consistent with the results of research on working capital management in conditions of uncertain demand (Levina et al., 2023). The observed reduction in operating costs when delegating fulfillment also corresponds to the conclusions of studies analyzing the effectiveness of outsourcing logistics services (Mohamed-Iliasse et al., 2022).

Speed vs. Assortment Trade-off: The hypothesis that the hybrid model allows for expanding the assortment matrix by 25-30% without increasing storage costs is confirmed. The "price" for this is an increase in the average delivery time for goods from the virtual warehouse by 2-3 days, which is critical for "impulse buy" product categories.

Control vs. Cost Trade-off: Delegating fulfillment to the supplier in the hybrid model leads to a 15-20% reduction in operational logistics costs. At the same time, a "coordination cost" arises—requiring investments in IT infrastructure for integrating and monitoring supplier order fulfillment. Research in effective multimodal logistics management emphasizes the importance of such investments for creating resilient hybrid systems (de Assis et al., 2024).

The table below presents the results of a comparative experiment with different levels of supplier reliability.

Table 2. Comparative Analysis of Profitability Under Different Supplier Reliability Scenarios .

Scenario (Reliability β)	Profit Architecture 1, rub.	Adjusted Profit Architecture 2, rub.	Expected Loss E_{loss}, rub.	Profit Deviation, %
Low Reliability (β = 0.85)	95 000	53 000	15 000	-44.2%
Medium Reliability (β = 0.90)	95 000	62 000	10 000	-34.7%
High Reliability (β = 0.95)	95 000	71 000	5 000	-25.3%
Ideal Supplier (β = 1.00)	95 000	80 000	0	-15.8%

The "Profit Deviation" column shows the percentage by which the profit of the hybrid model differs from the profit of the classical physical warehouse model. A negative value indicates that the hybrid model's profit is lower; this deviation demonstrates the price of the trade-off: we gain the advantages of the hybrid model in the form of released working capital and reduced risks of deadstock, but pay for it with a portion of the profit. The magnitude of this deviation directly depends on the supplier's reliability; the higher the β, value, the smaller the profitability gap between the two architectures. Based on such results, it is impossible to draw an unambiguous conclusion about the advantage of one architecture over the other, which emphasizes the necessity of an optimization approach. The problem statement is formulated concerning control variables – the vector *X*, characterizing the system configuration (e.g., distribution of the product assortment between physical and virtual channels, selection of suppliers, and determination of safety stock levels). The objective is to maximize the system's expected adjusted profit $P_{total}(X)$, which is the sum of the profit from the physical warehouse and the adjusted profit from the virtual channel, calculated considering the risk of supplier unreliability. For this objective function, the following constraints are identified:

The system's aggregate risk $R_{total}(X)$, calculated based on supplier reliability parameters (β) and the risk cost estimate *(R)*, must not exceed a set threshold $R_{\max}$.

The weighted average delivery time across all channels $T_{avg}(X)$ must not exceed the maximum allowable term $T_{\max}$, defined by the service policy.

The configuration *X* must satisfy constraints on the available volume of working capital and the storage capacity of the physical warehouse. The mathematical formulation is as follows: $P_{total}(X) \to \max$ subject to $R_{total}(X) \le R_{\max}$, $T_{avg}(X) \le T_{\max}$, $X \in \Omega$ (feasible resource region).

The formulated optimization problem statement is a logical outcome of the conducted analysis and offers a path to overcoming the identified trade-offs. The scientific novelty lies in the comprehensive approach to managing a hybrid warehouse architecture. Unlike classical models, the proposed formulation explicitly integrates key virtual warehouse parameters – supplier reliability and risk cost estimate – into the objective function and constraints. This allows not only for stating the existence of the "Liquidity vs. Risk" trade-off but also for managing it on a formal mathematical basis, finding a system configuration that maximizes profit at an acceptable risk level. The practical significance is that the model provides managers with a structured tool for strategic decision-making. Instead of an intuitive choice between architectures, it becomes possible to calculate the optimal allocation of assortment and resources. For example, calculation results similar to those presented in the table above show that including virtual warehouse goods in the assortment at $\beta > 0.9$ can be justified from a total risk perspective, while goods from unreliable suppliers $\beta < 0.85$ should be excluded or transferred to the physical warehous Within this work, the problem is presented in a verbal form. Its practical implementation requires solving a number of additional tasks. First, it is necessary to develop algorithms for numerical solution using methods of nonlinear or stochastic programming, accounting for the probabilistic nature of the parameter β. Second, the collection and analysis of real operational data for model calibration – empirical estimation of β and R values for various suppliers and product categories – is a relevant task. This defines promising directions for further research. For predicting future demand and inventory levels, the use of machine learning methods is planned, which are also successfully used in logistics (Nalgozhina and Uskenbayeva, 2023; Ilin et al., 2022), and automating hybrid business processes with RPA can optimize warehouse management (Egorov et al., 2021). For solving optimization problems, one could use, for example, the Pyomo library (https://www.pyomo.org/) for Python or other tools.

Conclusion

This work developed a comprehensive methodology for the comparative analysis of classical and hybrid warehouse architectures, including a system of financial, operational, and risk-oriented indicators. A mathematical framework was created, whose key element is the integration of risk parameters into the profit model. Using a conditional example, it was shown that accounting for risk significantly affects comparative efficiency. A verbal formulation of the optimization problem for managing a hybrid warehouse architecture was formulated, and promising directions for further research were identified. The conducted research demonstrates that the choice between classical and hybrid warehouse architecture represents a complex trade-off. As the comparative analysis showed, the reduction in operational costs and the release of working capital in the hybrid model are accompanied by a significant decrease in profitability, the magnitude of which directly depends on supplier reliability. This conclusion underscores the impossibility of a universal solution and confirms the necessity of an optimization approach to managing hybrid systems. The optimization problem statement developed in this work allows for overcoming the identified limitations.

REFERENCES

Antonov, A., Levina, A., Zhao, Z. 2025. Evolution of digital systems in the economy through the adoption of multi-agent technologies. In: Ilin, I., Youzhong, M. (eds.) Digital Systems and Information Technologies in the Energy Sector. DITES 2024. Lecture Notes in Networks and Systems 1244, 171–184. Springer, Cham. https://doi.org/10.1007/978-3-031-80710-7_14

Babkina A. 2024. Information investment platform as an improvement tool for investment climate of warehouse real estate. Technoeconomics 3, 2 (9), 85–98. DOI: https://doi.org/10.57809/2024.3.2.9.7

Christopher, M. 2016. Logistics & Supply Chain Management. 5th edn. Pearson, Harlow.

de Assis, R.F., Faria, A.F., Thomasset-Laperriиre, V., Santa-Eulalia, L.A., Ouhimmou, M., Ferreira, W.P. 2024. Machine learning in warehouse management: A survey. Procedia Computer Science 232, 2686–2695. https://doi.org/10.1016/j.procs.2024.02.096

Egorov, D., Levina, A., Kalyazina, S., Schuur, P., Gerrits, B. 2021. The challenges of the logistics industry in the era of digital transformation. In: Arseniev, D.G., et al. (eds.) Cyber-Physical Systems and Control. CPS&C 2020. Lecture Notes in Networks and Systems 259, 301–311. Springer, Cham. https://doi.org/10.1007/978-3-030-87966-2_27

Egorov, D., Shaban, A., Levina, A., Schuur, P., Gerrits, B., Levin, I. 2023. Digital methods of warehouse logistics as a tool to accelerate supply chains. In: Mottaeva, A. (ed.) E3S Web of Conferences 371, 05062. https://doi.org/10.1051/e3sconf/202337105062

Gelsomino, L.M., de Boer, R., Steeman, M., Perego, A. 2018. An optimisation strategy for concurrent Supply Chain Finance schemes. Journal of Purchasing and Supply Management 24(3), 201–211. https://doi.org/10.1016/j.pursup.2018.07.004

Gou, Q., Sethi, S., Yue, J., Zhang, J. 2016. Push and pull contracts in a local supply chain with an outside market. Decision Sciences 47(4), 625–653. DOI: https://doi.org/10.1111/deci.12209

Hasan, M.R., Daryanto, Y., Triki, C., Elomri, A. 2024. An inventory model of e-marketplace with a promotional program. Journal of Modelling in Management 19(3), 787–805. https://doi.org/10.1108/JM2-01-2023-0011

Iliashenko, V., Ilin, I., Schuur, P., Gerrits, B., Kalyazina, S., Esser, M. 2022. Business intelligence systems application in transport and logistics companies. In: Arseniev, D.G., et al. (eds.) Cyber-Physical Systems and Control II. CPS&C 2021. Lecture Notes in Networks and Systems 460, 670–680. Springer, Cham. https://doi.org/10.1007/978-3-031-20875-1_62

Ilin, I., Levina, A., Frolov, K. 2022. Innovative ecosystem model of vaccine lifecycle management. Journal of Open Innovation: Technology, Market, and Complexity 8(1), 5. https://doi.org/10.3390/joitmc8010005

Ivanov, D. 2020. Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transportation Research Part E: Logistics and Transportation Review 136, 101922. https://doi.org/10.1016/j.tre.2020.101922

Ivanov, D., Dolgui, A., Sokolov, B. 2022. Cloud supply chain: Integrating Industry 4.0 and digital platforms in the "Supply Chain-as-a-Service". Transportation Research Part E: Logistics and Transportation Review 160, 102676. https://doi.org/10.1016/j.tre.2022.102676

Ishfaq, R., Raja, U. 2017. Evaluation of order fulfillment options in retail supply chains. Decision Sciences 48(5), 866–894. https://doi.org/10.1111/deci.12277

Kong, X.T.R., Huang, G.Q., Du, M.L. 2019. A physical emulation model of cellular warehousing for e-commerce logistics. Procedia CIRP 81, 826–831. https://doi.org/10.1016/j.procir.2019.03.095

Levina, A., Frolov, K., Trifonova, N., Tick, A. 2023. Effective management of multimodal logistics in Russia. In: Ilin, I., et al. (eds.) Digital Technologies in Logistics and Infrastructure. DTLI 2023. Lecture Notes on Data Engineering and Communications Technologies 157, 279–291. Springer, Cham. https://doi.org/10.1007/978-3-031-24434-6_24

Li, G., Li, L., Sethi, S.P., Guan, X. 2022. Drop-shipping or self-holding? Strategic selection of the online fulfillment mode under competition. International Journal of Production Economics 244, 108380. https://doi.org/10.1016/j.ijpe.2021.108380

Li, M., Mizuno, S. 2022. A dual-channel supply chain model with inventory management. International Journal of Production Economics 244, 108382. https://doi.org/10.1016/j.ejor.2022.02.049

Mohamed-Iliasse, M.L., Benabbou, A., Berrado, A. 2022. Machine learning in supply chain management: A systematic literature review. International Journal of Supply and Operations Management 9(1), 1–22. https://doi.org/10.22034/ijsom.2021.109189.2279

Nalgozhina, N., Uskenbayeva, R. 2023. Automating hybrid business processes with RPA: optimizing warehouse management. Procedia Computer Science 221, 1474–1481. https://doi.org/10.1016/j.procs.2023.12.223

Soleimani, F., Pirayesh, M., Dehghanian, F. 2020. An integrated production-inventory model for a dual-channel supply chain. International Journal of Industrial Engineering & Production Research 31(3), 341–354.

Vandeput, N. 2020. Inventory optimization: Models and simulations. De Gruyter, Berlin.

Wang, Y., Zhang, D., Liu, Q., Shen, F., Lee, L.H. 2016. Towards enhancing the last-mile delivery: An effective crowd-tasking model with scalable solutions. Transportation Research Part E: Logistics and Transportation Review 93, 279–297. https://doi.org/10.1016/j.tre.2016.06.002

Wiedmer, R., Rogers, Z.S., Polyviou, M., Mena, C., Chae, S. 2021. The dark and bright sides of complexity: A dual perspective on supply network resilience. Journal of Business Logistics 42(3), 336–359. https://doi.org/10.1111/jbl.12264

Winkelmann, S., Spinler, S. 2022. The value of drop-shipping for managing demand uncertainty in e-commerce. Business Research 15(1), 267–296. https://doi.org/10.1007/s40685-021-00193-7

Xu, S., Tang, H., Lin, Z. 2021. Inventory and ordering decisions in dual-channel supply chains involving free riding and consumer switching behavior with supply chain financing. Mathematical Problems in Engineering 2021, 5530124. https://doi.org/10.1155/2021/5530124

СПИСОК ИСТОЧНИКОВ

Antonov, A., Levina, A., Zhao, Z. 2025. Evolution of digital systems in the economy through the adoption of multi-agent technologies. In: Ilin, I., Youzhong, M. (eds.) Digital Systems and Information Technologies in the Energy Sector. DITES 2024. Lecture Notes in Networks and Systems 1244, 171–184. Springer, Cham. https://doi.org/10.1007/978-3-031-80710-7_14

Babkina A. 2024. Information investment platform as an improvement tool for investment climate of warehouse real estate. Technoeconomics 3, 2 (9), 85–98. DOI: https://doi.org/10.57809/2024.3.2.9.7

Christopher, M. 2016. Logistics & Supply Chain Management. 5th edn. Pearson, Harlow.

de Assis, R.F., Faria, A.F., Thomasset-Laperriиre, V., Santa-Eulalia, L.A., Ouhimmou, M., Ferreira, W.P. 2024. Machine learning in warehouse management: A survey. Procedia Computer Science 232, 2686–2695. https://doi.org/10.1016/j.procs.2024.02.096

Egorov, D., Levina, A., Kalyazina, S., Schuur, P., Gerrits, B. 2021. The challenges of the logistics industry in the era of digital transformation. In: Arseniev, D.G., et al. (eds.) Cyber-Physical Systems and Control. CPS&C 2020. Lecture Notes in Networks and Systems 259, 301–311. Springer, Cham. https://doi.org/10.1007/978-3-030-87966-2_27

Egorov, D., Shaban, A., Levina, A., Schuur, P., Gerrits, B., Levin, I. 2023. Digital methods of warehouse logistics as a tool to accelerate supply chains. In: Mottaeva, A. (ed.) E3S Web of Conferences 371, 05062. https://doi.org/10.1051/e3sconf/202337105062

Gelsomino, L.M., de Boer, R., Steeman, M., Perego, A. 2018. An optimisation strategy for concurrent Supply Chain Finance schemes. Journal of Purchasing and Supply Management 24(3), 201–211. https://doi.org/10.1016/j.pursup.2018.07.004

Gou, Q., Sethi, S., Yue, J., Zhang, J. 2016. Push and pull contracts in a local supply chain with an outside market. Decision Sciences 47(4), 625–653. DOI: https://doi.org/10.1111/deci.12209

Hasan, M.R., Daryanto, Y., Triki, C., Elomri, A. 2024. An inventory model of e-marketplace with a promotional program. Journal of Modelling in Management 19(3), 787–805. https://doi.org/10.1108/JM2-01-2023-0011

Iliashenko, V., Ilin, I., Schuur, P., Gerrits, B., Kalyazina, S., Esser, M. 2022. Business intelligence systems application in transport and logistics companies. In: Arseniev, D.G., et al. (eds.) Cyber-Physical Systems and Control II. CPS&C 2021. Lecture Notes in Networks and Systems 460, 670–680. Springer, Cham. https://doi.org/10.1007/978-3-031-20875-1_62

Ilin, I., Levina, A., Frolov, K. 2022. Innovative ecosystem model of vaccine lifecycle management. Journal of Open Innovation: Technology, Market, and Complexity 8(1), 5. https://doi.org/10.3390/joitmc8010005

Ivanov, D. 2020. Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transportation Research Part E: Logistics and Transportation Review 136, 101922. https://doi.org/10.1016/j.tre.2020.101922

Ivanov, D., Dolgui, A., Sokolov, B. 2022. Cloud supply chain: Integrating Industry 4.0 and digital platforms in the "Supply Chain-as-a-Service". Transportation Research Part E: Logistics and Transportation Review 160, 102676. https://doi.org/10.1016/j.tre.2022.102676

Ishfaq, R., Raja, U. 2017. Evaluation of order fulfillment options in retail supply chains. Decision Sciences 48(5), 866–894. https://doi.org/10.1111/deci.12277

Kong, X.T.R., Huang, G.Q., Du, M.L. 2019. A physical emulation model of cellular warehousing for e-commerce logistics. Procedia CIRP 81, 826–831. https://doi.org/10.1016/j.procir.2019.03.095

Levina, A., Frolov, K., Trifonova, N., Tick, A. 2023. Effective management of multimodal logistics in Russia. In: Ilin, I., et al. (eds.) Digital Technologies in Logistics and Infrastructure. DTLI 2023. Lecture Notes on Data Engineering and Communications Technologies 157, 279–291. Springer, Cham. https://doi.org/10.1007/978-3-031-24434-6_24

Li, G., Li, L., Sethi, S.P., Guan, X. 2022. Drop-shipping or self-holding? Strategic selection of the online fulfillment mode under competition. International Journal of Production Economics 244, 108380. https://doi.org/10.1016/j.ijpe.2021.108380

Li, M., Mizuno, S. 2022. A dual-channel supply chain model with inventory management. International Journal of Production Economics 244, 108382. https://doi.org/10.1016/j.ejor.2022.02.049

Mohamed-Iliasse, M.L., Benabbou, A., Berrado, A. 2022. Machine learning in supply chain management: A systematic literature review. International Journal of Supply and Operations Management 9(1), 1–22. https://doi.org/10.22034/ijsom.2021.109189.2279

Nalgozhina, N., Uskenbayeva, R. 2023. Automating hybrid business processes with RPA: optimizing warehouse management. Procedia Computer Science 221, 1474–1481. https://doi.org/10.1016/j.procs.2023.12.223

Soleimani, F., Pirayesh, M., Dehghanian, F. 2020. An integrated production-inventory model for a dual-channel supply chain. International Journal of Industrial Engineering & Production Research 31(3), 341–354.

Vandeput, N. 2020. Inventory optimization: Models and simulations. De Gruyter, Berlin.

Wang, Y., Zhang, D., Liu, Q., Shen, F., Lee, L.H. 2016. Towards enhancing the last-mile delivery: An effective crowd-tasking model with scalable solutions. Transportation Research Part E: Logistics and Transportation Review 93, 279–297. https://doi.org/10.1016/j.tre.2016.06.002

Wiedmer, R., Rogers, Z.S., Polyviou, M., Mena, C., Chae, S. 2021. The dark and bright sides of complexity: A dual perspective on supply network resilience. Journal of Business Logistics 42(3), 336–359. https://doi.org/10.1111/jbl.12264

Winkelmann, S., Spinler, S. 2022. The value of drop-shipping for managing demand uncertainty in e-commerce. Business Research 15(1), 267–296. https://doi.org/10.1007/s40685-021-00193-7

Xu, S., Tang, H., Lin, Z. 2021. Inventory and ordering decisions in dual-channel supply chains involving free riding and consumer switching behavior with supply chain financing. Mathematical Problems in Engineering 2021, 5530124. https://doi.org/10.1155/2021/5530124

INFORMATION ABOUT AUTHOR / ИНФОРМАЦИЯ ОБ АВТОРЕ

ERMOCHENKO Semen A. – student.
E-mail: esemion10@gmail.com
ЕРМОЧЕНКО Семён Андреевич – студент.
E-mail: esemion10@gmail.com

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Телефон редакции 8 (812) 550-36-52

E-mail: technoeconomics@spbstu.ru

Компьютерная верстка *Д.М. Гугутишвили*
Редактирование английского языка *И.В. Ильина*
Ответственный секретарь *О.В. Воронова*
Выпускающий редактор *А.И. Лёвина*

Санкт-Петербургский политехнический университет Петра Великого.
195251, Санкт-Петербург, ул. Политехническая, д. 29.