INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

From Digital Activities to Business Value: Development of the Integrated DAEP Framework

Petra Cajnko[1]*, Kaja Cajnko[2]

[1]University of Maribor, Faculty of Natural Sciences and Mathematics, Maribor, Slovenia

[2]University of Maribor, Faculty of Arts, Maribor, Slovenia

DOI: https://doi.org/10.51583/IJLTEMAS.2026.150900005

Received: 16 September 2026; Accepted: 21 September 2026; Published: 29 September 2026

ABSTRACT

Digitalization enables firms to establish multiple digital touchpoints, collect data on user behavior, and apply analytical approaches to monitor and optimize business activities. Nevertheless, digital presence and the intensity of digital activities alone do not guarantee the creation of business value. This study aims to develop and empirically evaluate the integrated DAEP (Digital–Analytics–Experience–Performance) conceptual framework, which explains the process through which digital interactions and data are transformed into analytical insights, improvements in user experience and customer engagement, and measurable business outcomes. The study is based on a secondary analysis of four empirical studies and a structured cross-case synthesis of business cases in the areas of e-commerce, user experience, digital marketing, and web analytics. The analysis is conducted across the four components of the DAEP framework and the transitions between them, distinguishing among digital or operational, behavioral or relational, and business or financial outcomes. The findings indicate that the business value of digital activities depends not merely on their presence or intensity, but primarily on a firm's ability to transform digital data into analytical insights, use these insights in decision-making, and translate them into improvements in the digital experience and activities associated with customer responses and business outcomes. Empirical support for the individual relationships within the framework varies in strength. The clearest evidence concerns the importance of analytical interpretation of data, the translation of insights into optimization activities, and the distinction between digital activity and actual business value. Evidence is less direct for the complete mediating sequence linking user experience, behavioral responses, and financial outcomes, as well as for the continuous feedback loop. The theoretical contribution of the study lies in integrating areas that have largely been examined in a fragmented manner into the process-oriented and cyclical DAEP framework, thereby enabling analysis of the transitions through which digital activities may be transformed into business value.

Keywords: digital analytics; data-driven decision-making; user experience; customer engagement; business performance; DAEP framework.

INTRODUCTION

Digitalization has significantly transformed the ways in which firms create value, communicate with customers, shape user experiences, and monitor and evaluate business performance. Digital technologies are no longer merely a supporting infrastructure for individual business functions; rather, they are becoming an integral part of organizational processes, business models, and customer relationships (Hanelt et al., 2021). In the context of digital marketing, this development is reflected in the growing number of digital touchpoints through which firms simultaneously conduct marketing and sales activities while collecting data on user behavior and responses (Kannan & Li, 2017; Lemon & Verhoef, 2016).

The increasing volume of digital data has strengthened the importance of web and marketing analytics as well as data-driven decision-making. Digital channels enable firms to track visits, clicks, conversions, response rates, purchasing behavior, and other indicators; however, the availability of data alone does not ensure the creation of business value. The effectiveness of web analytics depends on a firm's ability to select relevant

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

metrics, interpret data appropriately, and integrate the resulting insights into decision-making processes (Järvinen & Karjaluoto, 2015). Similarly, research on data-driven management suggests that the potential of data is realized primarily when analytical capabilities are linked to organizational decision-making and action (Brynjolfsson et al., 2011).

Analytical insights, however, represent only one stage in the process of creating digital business value. Their value is realized only when they are translated into changes in digital activities, communication, and user experience. User experience develops across different stages of the customer journey and through numerous digital and other touchpoints and therefore cannot be reduced merely to the technical usability of a website (Lemon & Verhoef, 2016). The design of an effective online experience involves informativeness, functionality, navigation, social presence, sensory elements, and other characteristics of the digital environment, whose relevance also depends on the context of the interaction (Bleier et al., 2019). A positive user experience may be reflected in satisfaction, trust, engagement, purchasing behavior, and loyalty; however, the relationship between an individual digital improvement and the ultimate business outcome is generally not direct (Rose et al., 2012).

Digital communication and personalization also constitute important elements of this process. User data enable firms to segment customers more precisely, tailor content, and design more relevant digital touchpoints (Alves Gomes & Meisen, 2023). However, personalization alone does not guarantee a positive response, as its effectiveness also depends on perceived relevance, trust, and the manner in which data are collected and used (Aguirre et al., 2015). Similarly, customer engagement represents a multidimensional process that extends beyond an individual transaction and encompasses cognitive, emotional, and behavioral responses to interactions with a firm or brand (Brodie et al., 2013).

From a business decision-making perspective, it is therefore particularly important to distinguish between **digital activity and business performance**. Website visits, impressions, clicks, bounce rates, responses to email messages, and other digital metrics enable firms to monitor users' immediate responses, but they do not in themselves demonstrate the creation of business value. Marketing performance is a multidimensional construct whose appropriate assessment requires a clear definition of both the level and type of outcomes being measured (Katsikeas et al., 2016). Digital or operational metrics should therefore be linked to behavioral and relational outcomes at the customer level as well as to more distal business and financial outcomes. Research on customer satisfaction and loyalty likewise indicates that customer-level outcomes may be associated with firms' financial performance, although these effects are more distal and depend on multiple intervening factors (Mittal et al., 2023).

The existing literature thus provides extensive knowledge on digital transformation (Hanelt et al., 2021), digital marketing (Kannan & Li, 2017), web and marketing analytics (Agag et al., 2024; Järvinen & Karjaluoto, 2015), user experience and the customer journey (Bleier et al., 2019; Lemon & Verhoef, 2016), personalization and customer engagement (Aguirre et al., 2015; Brodie et al., 2013), and the measurement of marketing and business performance (Katsikeas et al., 2016; Mittal et al., 2023). Nevertheless, these areas are often examined from different theoretical perspectives and at different levels of analysis. Systematic literature reviews highlight the breadth and multidimensionality of the relationships among digital transformation, marketing, user experience, digital metrics, customer behavior, and organizational outcomes (Cioppi et al., 2023; Hanelt et al., 2021).

This gives rise to the research problem addressed in the present study. It remains less clear **how the individual stages of the digital business value creation process are interconnected**: how digital interactions generate data, how these data are transformed into analytical insights and decisions, how such decisions translate into changes in user experience and customer engagement, and how behavioral responses subsequently relate to measurable business outcomes. Of particular importance are the transitions between these stages, since the existence of an individual digital capability does not in itself ensure that its potential will be transferred to the next stage of value creation.

The aim of this study is therefore to develop an integrated conceptual framework that connects digital interactions and data, analytics and data-driven decision-making, user experience and customer engagement,

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

and different levels of performance. On this basis, the **Digital–Analytics–Experience–Performance (DAEP) Framework** is developed, conceptualizing these elements as an interconnected process of digital business value creation. The framework is empirically evaluated through a structured comparative synthesis of four existing empirical studies from different areas of digital business.

The scientific contribution of the study is threefold. First, it integrates several research streams that are often addressed separately in the literature into a unified process-oriented framework. Second, it shifts attention from individual digital capabilities to the **transitions between them**, thereby enabling the examination of points at which the business value creation process may be strengthened, weakened, or disrupted. Third, it adopts a multilevel perspective on performance by distinguishing among immediate digital or operational outcomes, behavioral and relational outcomes at the customer level, and ultimate business or financial outcomes. The study therefore does not assume that the individual elements of the framework represent novel concepts; rather, its contribution lies in systematically integrating them into a unified process-oriented framework.

Based on the research problem outlined above, the following research questions are formulated:

RQ1: Which digital and data-related capabilities of firms are associated with improved online business performance in the cases examined?

RQ2: What role does user experience play in linking firms' digital activities with user behavior, engagement, and purchasing decisions?

RQ3: How do web analytics and data-driven decision-making contribute to the optimization of digital marketing and sales activities?

RQ4: Which digital activities in the cases examined demonstrate a measurable association with business outcomes, and for which activities is this relationship weaker or less direct?

The remainder of the paper is structured as follows. First, the theoretical framework of the key concepts is presented, followed by the development of the DAEP conceptual framework and the derivation of the research propositions. The methodological approach and structured cross-case analysis of the empirical cases are then presented, followed by a discussion of the findings and a conclusion outlining the theoretical and managerial implications, research limitations, and directions for further empirical evaluation of the framework.

THEORETICAL FRAMEWORK

Digitalization, Digital Transformation, and Digital Marketing

Digitalization has significantly changed the ways in which firms create, deliver, and capture value. In this context, it is important to distinguish between the use of individual digital technologies and the broader process of digital transformation. Digital transformation represents organizational change triggered or shaped by digital technologies and may affect strategy, business processes, organizational structures, business models, and a firm's relationships with various stakeholders (Hanelt et al., 2021). Digitalization should therefore not be viewed merely as a technological process, but rather as a multidimensional phenomenon associated with organizational and managerial change (Calderon-Monge & Ribeiro-Soriano, 2024).

In the field of marketing, digital transformation is reflected in the development of new channels, touchpoints, modes of communication, and opportunities to monitor user behavior. Kannan and Li (2017) conceptualize digital marketing as a process enabled by digital technologies through which firms create, communicate, and deliver value to customers. The digital environment thus changes not only communication channels, but also the ways in which firms acquire customer information, design their offerings, manage relationships, and evaluate marketing outcomes.

The systematic review by Cioppi et al. (2023) further indicates that research on digital transformation and marketing has developed around several interconnected themes, including customer relationship management, customer engagement, digital metrics, user experience and the customer journey, process efficiency, marketing

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

technologies, market knowledge, communication, and consumer behavior. This breadth confirms that digital business cannot be adequately explained solely through the use of a particular digital channel or technology.

To understand the creation of business value, it is therefore important to distinguish among **digital presence, digital activity, and digital capability**. Digital presence refers to a firm's presence across digital channels; digital activity refers to the actual interactions and processes conducted through these channels; and digital capability refers to a firm's ability to systematically use digital technologies, data, and acquired knowledge in decision-making and value creation.

This distinction provides the basis for the theoretical argument developed in the following sections. Digital activities generate interactions and data, but their mere existence does not explain whether or how they contribute to improved business outcomes. To address this issue, it is necessary to examine the processes through which digital data are transformed into analytical insights and business decisions.

Web Analytics and Data-Driven Decision-Making

Digital interactions generate large volumes of data on user behavior, the effectiveness of digital channels, and the outcomes of marketing activities. However, the business value of these data is determined not by their volume, but primarily by a firm's ability to systematically collect, analyze, interpret, and use them in decision-making.

Järvinen and Karjaluoto (2015) conceptualize web analytics as an important mechanism for measuring digital marketing performance. Their research emphasizes that the use of web analytics is not limited to the technical collection of data but also involves selecting relevant metrics, processing information, and integrating it into organizational processes. It is therefore important to distinguish between **measuring digital activity** and **measurement-based management**. The former provides data, whereas the latter requires the interpretation and application of those data in decision-making.

The importance of data-driven decision-making extends beyond the field of marketing. Brynjolfsson et al. (2011) demonstrated a positive association between more intensive use of data-driven decision-making and organizational productivity and performance, suggesting that data create greater value when they become an integral part of managerial decision-making.

In the field of marketing, Agag et al. (2024) link analytical capabilities to a firm's ability to respond effectively to changes in customer needs. Their findings indicate that the relationship between the use of marketing analytics and customer satisfaction is not necessarily direct, but may be realized through organizational capabilities that translate analytical insights into appropriate action. Similarly, Mehrabi et al. (2024) emphasize the importance of a data-driven culture and customer orientation in developing **customer analytics capabilities**.

On this basis, the analytical process can be conceptualized as a sequence of five interconnected activities: **data generation and collection → metric selection and measurement → analysis and interpretation → translation of insights into decisions → monitoring the effects of decisions**. Analytics is therefore not merely a system of retrospective reporting, but rather a transformational mechanism through which digital interactions can become a foundation for organizational learning and action.

However, even a high-quality analytical insight does not in itself constitute a business outcome. Its value depends on whether the firm translates it into changes in the digital environment, its offering, communication, or other customer touchpoints. **User experience therefore represents the next important stage in the process.**

User Experience in the Digital Environment

User experience represents an important link between a firm's digital capabilities and customer responses. In the digital environment, it cannot be reduced solely to the technical usability of a website or application.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

Rather, it encompasses a broader set of cognitive, emotional, perceptual, and behavioral responses that arise when users interact with a firm's digital environment (Rose et al., 2012).

In this context, it is useful to distinguish between **user experience (UX)** and the broader concept of **customer experience (CX)**. UX is more directly related to a user's interaction with a digital interface, including its usability, comprehensibility, functionality, and perceived quality, whereas CX encompasses the broader customer journey across different touchpoints before, during, and after a purchase (Lemon & Verhoef, 2016; Norman, 2013).

Lemon and Verhoef (2016) emphasize that customer experience develops throughout the entire customer journey and across various touchpoints, which are not always directly controlled by the firm. Digital experience is therefore not the result of a single website characteristic, but rather a combination of information, functionality, communication, prior experiences, and the context of the interaction.

In their experimental research on online customer experience, Bleier et al. (2019) identified four broad dimensions involved in designing an effective online experience: informativeness, entertainment, social presence, and sensory appeal. Their findings also indicate that the effects of individual web design elements are not universal but depend on the context, product characteristics, and trust in the brand.

For online business, particularly important factors include clarity of information, intuitive navigation, high-quality product presentation, ease of completing desired actions, mobile usability, and the reduction of user uncertainty. Homburg et al. (2017) further position user experience within the broader concept of customer experience management, which requires organizational capabilities for the systematic design and management of different touchpoints.

In relation to analytics, this means that data on user behavior can help identify points of friction, process abandonment, insufficient relevance, or other problems along the user journey. Analytical insights can therefore provide a basis for the iterative improvement of user experience.

At the same time, this relationship is cyclical. Changes in user experience generate new interactions and behavioral responses, which in turn create new data for further analysis. This results in a process of **data → analysis → changes in experience → behavioral response → new data**, providing an important basis for understanding continuous digital optimization.

Digital Communication, Personalization, and Customer Engagement

The digital environment enables firms to tailor their communication with customers based on data about their behavior, characteristics, and previous interactions. Websites, email marketing, social media, mobile applications, and other digital channels therefore function not merely as distribution or communication channels, but as touchpoints through which customers' experiences and relationships with firms are shaped (Lemon & Verhoef, 2016).

The effectiveness of digital communication depends on its relevance, content, timing, and execution. In the context of email marketing, Ellis-Chadwick and Doherty (2012) emphasize that message design and content significantly influence how recipients interact with marketing communications.

Advances in analytical methods also enable firms to segment users more precisely and engage them through personalized communication. In their review of customer segmentation methods, Alves Gomes and Meisen (2023) present a broad range of data-driven approaches that enable more precisely targeted activities in e-commerce. Personalization can therefore serve as a mechanism through which firms translate analytical knowledge into a more relevant digital experience.

However, the effects of personalization are not necessarily always positive. Through the concept of the personalization paradox, Aguirre et al. (2015) demonstrate that greater personalization can increase the effectiveness of digital advertising, while the way in which information is collected and used may

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

simultaneously raise privacy concerns. Trust therefore represents an important condition for translating data-driven personalization into a positive user experience.

Weidig et al. (2024) place personalized touchpoints within the broader context of customer experience and emphasize that their effects cannot be understood independently of customer characteristics, context, and the stage of the customer journey. Personalization is therefore not an end in itself, but rather one of the potential mechanisms through which data and analytical insights can be translated into more relevant interactions.

The next stage in this process is **customer engagement**. Brodie et al. (2013) conceptualize customer engagement as a dynamic and multidimensional process encompassing cognitive, emotional, and behavioral dimensions of the customer's relationship with a brand. Engagement therefore extends beyond an individual transaction and may include interaction with content, participation, recommendations, repeated interactions, and other forms of active involvement.

The meta-analytic findings of Blut et al. (2023) further indicate that the effectiveness of customer engagement initiatives varies across platforms and circumstances. This again confirms that a firm's mere presence on a digital channel does not ensure effective customer engagement.

Within the process of digital value creation, digital communication and personalization can therefore be understood as **activation mechanisms** through which analytical insights are translated into concrete customer interactions, while engagement represents a behavioral and relational response that may link user experience to subsequent business outcomes.

From Digital Activities to Business Performance

The ultimate purpose of digital, analytical, and customer-oriented activities is to create value for both customers and firms. However, measuring this value is methodologically challenging because different metrics represent different levels of outcomes.

Järvinen and Karjaluoto (2015) emphasize the need to link digital metrics to actual marketing and business objectives. A website visit, an advertisement impression, a click, or the opening of an email message represents a measurable digital response, but does not in itself demonstrate a purchase, loyalty, or generated revenue.

Based on an extensive review of empirical research on marketing performance, Katsikeas et al. (2016) highlight substantial heterogeneity in the conceptualization and operationalization of performance outcomes. Appropriate performance assessment therefore requires a clear distinction between different types of outcomes and the levels at which they occur.

For the purposes of an integrated understanding of digital business value, outcomes can be classified into three levels.

Digital or operational performance includes immediate metrics of digital behavior and the effectiveness of specific activities, such as visits, impressions, clicks, click-through rates, time on page, bounce rates, email open rates, and shopping cart abandonment.

Customer-level performance includes behavioral and relational outcomes such as conversion, purchase, repeat purchase, customer retention, satisfaction, recommendation, engagement, and loyalty.

Business or financial performance includes outcomes such as revenue, sales growth, profit, profitability, market share, and other indicators of ultimate business value.

This distinction is important because an effect at one level does not automatically imply an effect at the next. In their meta-analytic synthesis spanning several decades of research, Mittal et al. (2023) identify positive associations among customer satisfaction, loyalty behaviors, and firms' financial performance; however, firm-level effects are more distal and depend on multiple intervening processes.

Therefore, understanding digital performance requires examining the **value creation chain** rather than individual metrics in isolation. A digital activity may generate a measurable operational response, which may subsequently translate into a behavioral customer outcome and only then into a business or financial outcome. At each transition, the effect may be strengthened, weakened, or lost.

This distinction provides an important theoretical foundation for the integrated framework, as it enables a clear differentiation between digital activity and actual business value.

Integration of Theoretical Concepts and the Research Gap

The literature review indicates that digital transformation, digital marketing, web and marketing analytics, data-driven decision-making, user experience, personalization, customer engagement, and performance measurement are well-established fields of research. At the same time, however, these fields have developed within different disciplinary and theoretical traditions and often employ different units and levels of analysis.

Systematic literature reviews confirm the multidimensional nature of digital transformation and digital marketing while also highlighting the fragmentation of research streams addressing the technological, organizational, marketing, and user-related dimensions of digitalization (Cioppi et al., 2023; Hanelt et al., 2021). Although Kannan and Li (2017) provide a broader framework for digital marketing, understanding business value requires further clarification of how different organizational and customer-related levels are interconnected in the process through which digital activities are translated into outcomes.

Based on the literature review, four interconnected conceptual challenges can be identified.

The first concerns the **transition from digital activity to business value**. Digital metrics enable the precise monitoring of interactions, but they do not in themselves explain how these interactions contribute to behavioral and financial outcomes (Järvinen & Karjaluoto, 2015; Katsikeas et al., 2016).

The second concerns the **transition from analytical insight to organizational action**. Data and analytics can improve decision-making, but value creation depends on the firm's ability to translate the resulting insights into actual changes (Agag et al., 2024).

The third concerns the **role of user experience and customer engagement as intermediate mechanisms**. The literature extensively addresses user experience, the customer journey, personalization, and engagement; however, it remains less clear how these elements are systematically integrated into the broader process linking analytics to business outcomes (Brodie et al., 2013; Lemon & Verhoef, 2016; Weidig et al., 2024).

The fourth challenge concerns the **multilevel measurement of performance**. Immediate digital metrics, customer behavioral outcomes, and financial outcomes represent different levels of performance and therefore cannot be treated as interchangeable indicators (Katsikeas et al., 2016; Mittal et al., 2023).

The research gap therefore does not lie in an absence of research on the individual components, but rather in the need for a more integrated, process-oriented understanding of how these components are interconnected. Of particular importance are the **transitions** through which digital interactions and data are transformed into analytical insights, analytical insights into changes in user experience and customer engagement, and behavioral responses into measurable business value.

On this basis, the integrated DAEP conceptual framework is developed in the following section. Its purpose is not to replace existing theories of digital marketing, analytics, or user experience, but rather to integrate their key elements into a process-oriented framework that enables the systematic examination of digital business value creation.

Daep Conceptual Framework And Research Propositions

Conceptual Design of the DAEP Framework

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

Based on the theoretical foundations and the identified research gap, the **Digital–Analytics–Experience–Performance (DAEP) Framework** is developed as an integrated conceptual framework for digital business value creation. The framework connects four interdependent components: **Digital Interaction and Data (D), Analytics and Data-Driven Decision-Making (A), Experience and Engagement (E), and Performance (P)**.

The underlying premise of the framework is that the business value of digitalization does not arise automatically from the adoption of digital channels and technologies or from increased digital activity. Digital interactions generate data, but their value depends on analytical interpretation and the integration of resulting insights into decision-making (Järvinen & Karjaluoto, 2015). Analytical insights must then be translated into organizational responses that affect digital touchpoints, communication, user experience, and customer engagement (Agag et al., 2024; Lemon & Verhoef, 2016). Behavioral and relational customer responses subsequently provide the basis for broader business outcomes, while different levels of performance need to be clearly distinguished (Katsikeas et al., 2016; Mittal et al., 2023).

The framework therefore assumes the following basic process logic:

D → A → E → P

where the individual components are defined as follows:

D – Digital Interaction and Data

The D component represents the digital touchpoints and activities through which data on interactions between firms and users are generated. It includes websites and online stores, email communication, social media, digital advertising, loyalty programs, and other digital sales and communication channels. D represents the input level of the framework: digital activities generate data potential, but do not in themselves ensure the creation of business value.

A – Analytics and Data-Driven Decision-Making

The A component represents the capability to transform digital data into information, analytical insights, and decisions. It includes the selection of relevant metrics, the analysis of behavioral and business data, the interpretation of results, and their application in planning and optimizing activities. Within the DAEP framework, analytics serves as a **transformational mechanism**, linking data generation to organizational action.

E – Experience and Engagement

The E component represents the way in which analytically informed decisions are manifested in interactions with customers. It encompasses user experience, the functionality and content of digital touchpoints, personalization, digital communication, and behavioral and relational forms of customer engagement. The E component therefore links organizational action to user responses and represents an intermediate level between analytical decision-making and performance outcomes (Brodie et al., 2013; Lemon & Verhoef, 2016).

P – Performance

The P component represents the measurable outcomes of digital activities and, due to their multidimensional nature, is divided into three analytical levels:

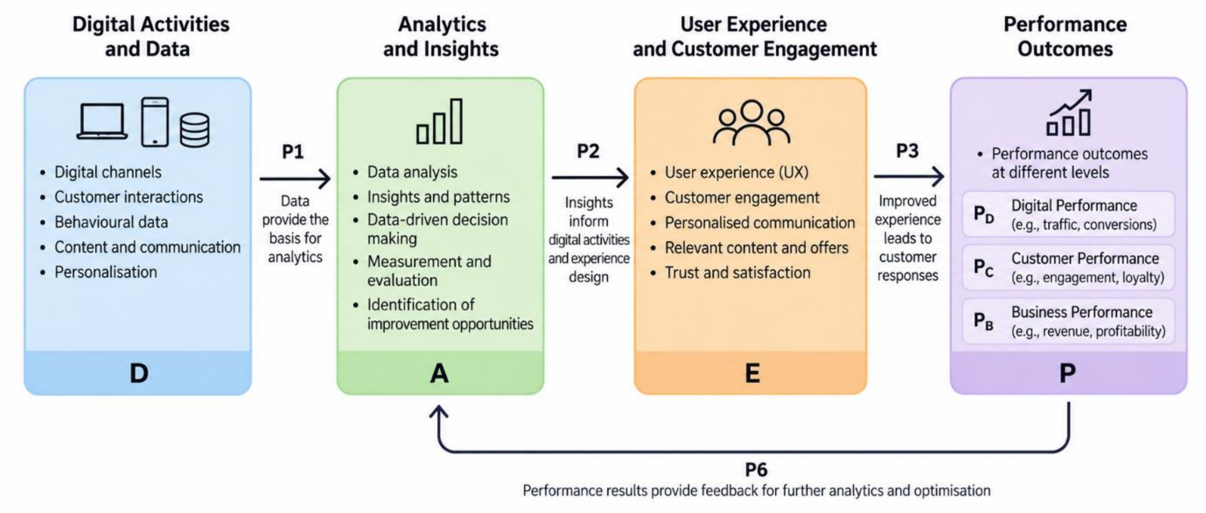
- **P_D – Digital Performance:** immediate digital or operational indicators, such as visits, clicks, response rates, bounce rates, and shopping cart abandonment;
- **P_C – Customer Performance:** behavioral and relational outcomes at the customer level, such as conversion, satisfaction, repeat purchase, retention, engagement, and loyalty;

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

- **P_B – Business Performance:** business or financial outcomes, such as revenue, sales growth, transactions, profit, and other indicators of business value.

The distinction among **P_D, P_C, and P_B** is important because an improvement in an immediate digital indicator does not necessarily imply an improvement in business or financial performance. The framework therefore does not assume an automatic transfer of effects across the different levels of performance.

Figure 1. Conceptual Model of the Digital–Analytics–Experience–Performance (DAEP) Framework



Source: Authors’ own elaboration.

The DAEP framework is therefore process-oriented, but not exclusively linear. The outcomes of digital activities generate new data that can be reintegrated into the analytical process and lead to further adjustments. This potential feedback loop enables digital optimization to be conceptualized as an iterative process of organizational learning; however, the continuity and effectiveness of this loop require longitudinal empirical validation.

Transitions Between the Components of the Framework

The central analytical feature of the DAEP framework lies not only in its four components, but primarily in the **transitions between them**. Business value may be lost or weakened at any stage of the process.

The first transition, **D → A**, represents the transformation of digital interactions and data into analytical insights. A firm may generate large volumes of digital data; however, without appropriate measurement, interpretation, and use in decision-making, these data remain largely an underutilized information resource. The capability for data-driven decision-making therefore represents a prerequisite for transforming digital activity into organizational knowledge (Brynjolfsson et al., 2011; Järvinen & Karjaluoto, 2015).

The second transition, **A → E**, represents the transformation of analytical insights into organizational responses that affect user experience, communication, personalization, or other digital touchpoints. Analytics alone does not change customer behavior; value is created only when the firm acts appropriately on the knowledge acquired. Research on marketing analytics indicates that its impact on customer outcomes may be realized through a firm's capability to respond to customer needs (Agag et al., 2024).

The third transition, **E → P**, represents the relationship between user experience or customer engagement and measurable outcomes. A positive experience may be associated with user behavior; however, it is necessary to distinguish among immediate digital responses, behavioral and relational outcomes, and ultimate business outcomes (Katsikeas et al., 2016; Lemon & Verhoef, 2016; Mittal et al., 2023).

The fourth transition, **P → A**, represents the feedback loop. The outcomes of previous activities generate new data on user behavior and business effects. Reanalyzing these data enables firms to evaluate implemented

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

actions and formulate subsequent decisions. In this way, the linear sequence D → A → E → P becomes an iterative process of measurement, interpretation, action, and reevaluation.

The process of digital business value creation can therefore be expressed as:

digital interactions → data → analytical insights → data-driven decisions → adaptation of digital experience and communication → behavioral and relational customer responses → business outcomes → new data.

The framework also enables the identification of different forms of process disruption. Digital activity may generate data without systematic analysis; an analytical insight may not result in an organizational response; or an improvement in digital experience may generate a behavioral response without a corresponding financial effect. The DAEP framework therefore does not attribute business value to any individual component, but rather to a firm's ability to effectively connect the successive stages of the process.

Research Propositions

Based on the conceptual logic of the DAEP framework, six research propositions are formulated. Because the study is based on a secondary comparative analysis of heterogeneous empirical studies, the propositions are not formulated as statistical hypotheses, but rather as theoretically grounded statements whose empirical support is assessed in the subsequent analysis.

P1: The business value of digital interactions depends on a firm's ability to systematically transform data generated through digital channels into analytical insights and use them in decision-making.

P1 derives from the **D → A** transition and assumes that the generation of digital data represents a necessary but not sufficient condition for business value creation. What is crucial is the transformation of these data into organizationally useful knowledge (Brynjolfsson et al., 2011; Järvinen & Karjaluoto, 2015).

P2: The effect of analytical capabilities on digital business value is realized through the transformation of analytical insights into concrete improvements in user experience and digital activities.

P2 refers to the **A → E** transition and assumes that analytical capabilities create value through organizational response. Analytical insights must be translated into changes in digital experience, communication, personalization, or other activities that users perceive or respond to (Agag et al., 2024).

P3: Positive changes in user experience are associated with more favorable behavioral and relational customer responses, including higher levels of engagement, satisfaction, trust, conversion, and loyalty.

P3 represents the first part of the **E → P** transition. It is based on the assumption that the quality of the digital experience is associated with the way users interact with the firm and may be reflected in various digital and behavioral outcomes (Bleier et al., 2019; Lemon & Verhoef, 2016; Rose et al., 2012).

P4: Behavioral and relational outcomes at the customer level represent an intermediate mechanism between improved digital user experience and the firm's business or financial outcomes.

P4 extends the **E → P** transition by distinguishing between **P_C and P_B**. It assumes that the ultimate business effect of user experience is generally not direct, but is realized through customer behavior and customer relationships. This understanding is consistent with findings regarding the relationships among customer satisfaction, loyalty, and firms' financial performance (Mittal et al., 2023).

P5: A high level of digital activity does not in itself ensure high business performance; digital metrics provide greater explanatory value when they are linked to customer behavioral outcomes and ultimate business indicators.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

P5 is based on the distinction among **P_D, P_C, and P_B**. It assumes that individual digital metrics cannot be directly interpreted as indicators of business success unless their relationship with behavioral and business outcomes is established (Järvinen & Karjaluoto, 2015; Katsikeas et al., 2016).

P6: A firm's greater capability to systematically reintegrate behavioral and business outcomes into the analytical process is theoretically expected to support the iterative optimization of digital activities and user experience.

P6 represents the **P → A** feedback relationship and the cyclical nature of the framework. The outcomes of previous activities are not treated merely as final outcomes, but as new data inputs for further analysis, decision-making, and adaptation.

Relationship Between the Research Questions and Research Propositions

The research questions and propositions serve different but complementary roles in the study. The research questions define the broader areas of empirical investigation, whereas the propositions operationalize the key relationships proposed by the DAEP conceptual framework.

Table 1. Relationship Between the Research Questions and Research Propositions

Research Question	**Core Focus**	**Primarily Related Propositions**
RQ1	Digital and data-related capabilities and online business performance	**P1, P2**
RQ2	Role of user experience in user behavior, engagement, and purchasing decisions	**P2, P3, P4**
RQ3	Web analytics, data-driven decision-making, and optimization	**P1, P2, P6**
RQ4	Relationship between digital activities and behavioral and business outcomes	**P4, P5**

This alignment enables the structured cross-case analysis to simultaneously address the broader research questions and assess the empirical support for the individual process relationships proposed by the framework. Accordingly, in the methodology section, the **D, A, E, and P components**, the transitions between them, and **propositions P1–P6** are used as the analytical framework for coding and comparing the findings of the included empirical studies.

METHODOLOGY

Research Design

The study is based on a **structured secondary analysis of existing empirical studies and a comparative analysis of multiple business cases (cross-case analysis)**. This approach was selected because the research objective is not to conduct a new statistical analysis of a single dataset, but rather to systematically compare the findings of substantively related yet methodologically heterogeneous empirical studies.

In the present study, secondary analysis involves the analytical reuse of documented empirical findings from previously conducted studies to address a new research question and assess the DAEP conceptual framework (Heaton, 2008; Ruggiano & Perry, 2019). Secondary analysis is not used here to combine individual

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

participants from different studies into a single sample, but rather to compare empirical findings at the level of individual research cases.

Accordingly, the research design **is not a meta-analysis**. The included studies differ in terms of research context, methods, units of observation, sample sizes, data sources, and performance indicators. Consequently, calculating a pooled effect or combining the results into a single statistical sample would not be methodologically justified. Instead, a structured comparative approach is employed to identify similarities, differences, recurring patterns, and contradictory findings across cases. This logic is consistent with the use of multiple cases for theory development and the analytical refinement of theoretical explanations (Eisenhardt, 1989; Eisenhardt & Graebner, 2007; Yin, 2018).

The DAEP conceptual framework was developed through the theoretical synthesis of the literature presented in the preceding section. The empirical studies were subsequently used to systematically assess the extent to which their findings provide support for the individual components, transitions, and research propositions of the framework. This approach analytically distinguishes the **theoretical derivation of the framework** from its **empirical evaluation**.

Selection of Empirical Studies

The empirical corpus comprises four independent studies conducted as part of final or diploma research projects at GEA College in 2026. The studies address different but conceptually related aspects of digital business: user experience in online stores, the redesign of online presence and digital marketing activities, the use of web analytics in email marketing, and the performance of various online sales and marketing activities.

At the time of preparation of the present article, the individual works differed in their formal status. The study by Starman (2026) had been completed and bibliographically recorded; the works by Spasojević (2026) and Koščak (2026) had been completed in terms of content and were in the process of defense; and the work by Frlan (2026) was still in preparation. These statuses are relevant primarily with regard to the formal status and accessibility of the source works. Regardless of the status of each work, the comparative analysis included only those empirical findings that had already been documented in the corresponding research materials at the time the secondary analysis was conducted and that met the predefined inclusion criteria.

The studies were selected purposively (**purposive selection**) based on their relevance to the research problem and the extent to which their findings could be mapped onto the components of the DAEP framework. The purpose of the selection was not to achieve statistical representativeness of digital business research, but rather to construct a conceptually diverse corpus of cases that enables the examination of different stages in the digital business value creation process.

The following inclusion criteria were applied:

1. the study includes an empirical component;
2. it examines at least one form of digital interaction or digital business activity;
3. it contains data or findings related to analytics, user experience, digital communication, customer behavior, or business performance;
4. its findings can be linked to at least two components of the DAEP framework or to a transition between them;
5. the research materials provide sufficient information on the research procedure, data, and results to enable structured comparison;
6. the results allow for the identification of relationships, differences, or contradictory findings relevant to the research questions and propositions.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

Based on these criteria, the studies by Starman (2026), Frlan (2026), Spasojević (2026), and Koščak (2026) were included in the analysis. Their conceptual complementarity enables the examination of different parts of the DAEP process, while no single study covers all components of the framework to the same extent.

Table 2. Characteristics of the Included Empirical Studies

Study	Research Context	Main Data Source or Method	Primarily Relevant DAEP Components	Source Status
Starman (2026)	User experience and sales performance of online stores	Comparative analysis of five Slovenian online stores and UX/performance indicators	D, A, E, P	Completed and bibliographically recorded diploma thesis
Frlan (2026)	Redesign of online presence and marketing strategies	Survey research (n = 92) and web analytics	D, A, E, P	Diploma thesis in preparation
Spasojević (2026)	Optimization of email marketing campaigns	Internal email campaign data; 10,910 emails sent	D, A, E, P	Final thesis submitted for defense
Koščak (2026)	Online sales, digital sales channels, and marketing activities	Business and sales data and comparison of digital activities	D, A, P	Final thesis submitted for defense

The heterogeneity of the cases was treated as an analytical feature of the research design, as it enables an assessment of the applicability of the conceptual framework across different digital contexts. At the same time, this heterogeneity limits the direct comparability of the results; therefore, the findings were not aggregated into common numerical indicators.

Unit of Analysis

The primary unit of analysis is not the individual respondent from the original studies, but rather the **empirical case and, within each case, an individual finding or set of findings relevant to the DAEP framework**.

This definition is important because of the differences among the original studies. An individual study may be based on survey data, web analytics data, internal business data, comparisons between firms, or a combination of multiple data sources. Consequently, combining individual respondents or observations across studies would not be methodologically appropriate.

The analysis was conducted at two levels. At the first level, a **within-case analysis** was performed to identify the research context, data used, key digital activities, analytical procedures, changes in user experience or communication, and reported outcomes. At the second level, a **cross-case analysis** was conducted to identify recurring patterns, differences, and contradictory evidence across the studies (Eisenhardt, 1989; Yin, 2018).

Analytical Framework and Coding Procedure

The analysis was conducted using a structured analytical matrix developed on the basis of the DAEP conceptual framework. For each included study, relevant findings were classified according to the four components of the framework:

D – Digital Interaction and Data: digital channels, activities, interactions, and data sources;

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

A – Analytics and Data-Driven Decision-Making: measurement, analysis, interpretation of data, and their use in decision-making;

E – Experience and Engagement: user experience, communication, personalization, and behavioral and relational user responses;

P – Performance: measurable outcomes, further classified into:

- **P_D – Digital Performance**;
- **P_C – Customer Performance**;
- **P_B – Business Performance**.

In addition to the individual components, evidence concerning the transitions **D → A, A → E, E → P, and P → A** was analyzed separately.

For each relevant empirical finding, the analytical matrix recorded the following information: the source study, research context, data source or method used, relevant DAEP component, level of performance, potential transition between components, relationship to a research proposition, type of empirical evidence, and methodological limitations affecting its interpretation.

The coding procedure was **theory-driven**, as the main categories D, A, E, and P were defined on the basis of the previously developed conceptual framework. At the same time, the analysis was not restricted solely to findings supporting the framework. Results indicating weak, absent, or contradictory relationships between digital activities and the expected outcomes were also systematically recorded.

This approach is important for reducing the risk of confirmation bias. The empirical cases were therefore used not merely to illustrate the DAEP framework, but also to identify **where the proposed process logic is not supported or is only partially supported**.

Comparative Analysis of Empirical Evidence

Following the coding of findings from the individual studies, a structured cross-case comparison was conducted. The comparison was guided by four analytical questions:

1. Which digital channels and activities generate data relevant to subsequent decision-making (**D**)?
2. How are the data analyzed, and to what extent are they used to inform decisions (**D → A**)?
3. How and to what extent are analytical insights translated into changes in user experience, communication, or other digital activities (**A → E**)?
4. What digital, behavioral, and business outcomes accompany the analyzed activities, and are these outcomes reintegrated into subsequent analysis (**E → P; P → A**)?

Particular attention was paid to distinguishing between **the co-occurrence or association of changes and evidence of causality**. When an original study reported a change in a digital activity accompanied by a change in an outcome, but the research design did not allow the effect of the individual intervention to be isolated, the finding was interpreted as an association or as empirical consistency with the framework rather than as evidence of a causal effect.

Negative or deviant cases were also retained in the analysis. An activity for which the expected business effect was not observed was not treated as an irrelevant result, but rather as analytically important evidence for assessing the boundaries of the framework and, in particular, for distinguishing between digital activity and business performance.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

Assessment of the Research Propositions

Empirical support for propositions P1–P6 was assessed by comparing evidence across all four studies. Given the heterogeneity of the data and research designs, the propositions were not statistically tested.

For each proposition, a four-level descriptive assessment was applied:

- **supported** – when findings from multiple cases were consistent with the proposed relationship and no substantial contradictory evidence was identified;
- **partially supported** – when relevant supporting evidence was available, but the relationship was not directly examined across all necessary stages or the evidence was limited;
- **not supported** – when the available empirical evidence predominantly contradicted the proposed relationship;
- **cannot be assessed** – when the included studies did not provide sufficient evidence to support a reasoned assessment.

This assessment does not represent the statistical confirmation or rejection of the propositions, but rather a **structured evaluation of the consistency of the existing empirical findings with the conceptual logic of the DAEP framework**.

Ensuring Analytical Transparency and Rigor

To enhance the transparency of the analysis, a traceable link was established between the original findings, their coding into the DAEP components, and the final interpretation of the research propositions. The interpretation took into account whether a finding was based on survey data, behavioral or analytical metrics, business data, or a combination of multiple data sources.

The comparative analysis was not based on counting the number of supporting findings. Multiple findings from the same study do not constitute multiple independent pieces of evidence. Instead, emphasis was placed on the **consistency of patterns across studies, the directness of the relationship to the proposition under examination, the type of data used, and the limitations of the original research design**.

Particular analytical weight was given to cases in which a digital activity was not associated with the expected business outcome, as such cases enable a critical assessment of the assumption that increased digital activity automatically leads to improved business performance.

Because the analysis is based on secondary sources employing different methodological designs, the study does not claim inter-coder reliability or other procedures that were not actually applied. Rigor is instead grounded primarily in a transparent analytical framework, systematic cross-case comparison, the retention of contradictory evidence, and careful differentiation between empirical association and causality.

Ethical Considerations and Methodological Limitations

The study does not involve new data collection from participants but is based on a secondary analysis of findings from four previously conducted empirical studies. The units of analysis are the reported or documented findings of the individual research cases rather than individual-level participant data.

The original studies differ in their formal and bibliographic status. At the time of preparation of this article, one of the works included in the analysis had been completed and bibliographically recorded, two had been submitted for defense, and one was still in preparation. To ensure research transparency, the authorship, research context, and status of each source are clearly stated. The use of unpublished research materials is limited to documented results relevant to the comparative analysis, and no additional individual-level participant data that could enable the identification of participants were used.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

The methodological limitations of the study arise primarily from the secondary nature of the analysis and the heterogeneity of the included studies. The original studies were not designed to directly test the DAEP framework; consequently, its components and process transitions are not equally represented across all cases. The studies also differ in terms of research methods, sample sizes, business contexts, data sources, and performance indicators. Direct numerical pooling of the results is therefore not methodologically justified, nor can the findings be interpreted as a statistical test of the framework as a whole.

An additional limitation arises from the research designs of the original studies, which generally do not allow the effects of individual digital activities to be isolated. Observed changes in digital, behavioral, or business outcomes are therefore interpreted as associations or as empirical consistency with the proposed relationships of the DAEP framework rather than as evidence of causal effects. Consequently, the study does not allow for the estimation of pooled effect sizes or the establishment of causal relationships among the individual components of the framework.

An important limitation also concerns the formal status and accessibility of some of the empirical sources. At the time of preparation of this article, not all of the included final or diploma theses had been publicly available or formally completed. The analysis therefore relies in part on documented research materials available to the authors at the time the secondary analysis was conducted. This limits the possibility of direct independent verification of some of the source material and requires appropriate caution in interpreting the findings.

Despite these limitations, the methodological value of the study lies in the structured comparative assessment of the conceptual framework based on heterogeneous empirical evidence, the systematic differentiation among supportive, partial, and contradictory findings, and the analytical distinction between association and causality. The results therefore primarily provide a foundation for further purpose-designed empirical testing of the DAEP framework using research designs that enable more direct examination of individual process relationships and of the framework's complete feedback loop.

RESULTS

Overview of the Empirical Cases

The structured cross-case analysis included four empirical studies addressing different aspects of digital business and enabling the examination of individual components and transitions within the DAEP framework. The studies differ in terms of business context, data sources, methods, and performance indicators. Their results were therefore not directly pooled numerically, but were compared at the level of empirical findings.

Starman (2026) examined the impact of key user experience elements on the sales performance of five Slovenian online stores: OneDrone, SWY, SnowMonkey, Pharmagea, and Vezenina. The analysis covered elements such as navigation, search functionality, product presentation, personalization, and mobile optimization, as well as their associations with online performance indicators. In individual cases, changes in conversion rates, bounce rates, and shopping cart abandonment were observed following modifications to user experience elements.

Frlan (2026) examined the redesign of the online presence and marketing strategies of Sivka zdravo življenje d.o.o. The study combined survey data from 92 participants with web analytics data. The changes examined included the visual and functional redesign of the firm's online presence, modifications to digital marketing activities, and changes in customer communication. Because several interventions were implemented simultaneously, their individual effects cannot be reliably isolated. The analysis is based on the versions of the research materials available to the authors of this article as of 16 September 2026; any subsequent changes to works that had not yet been completed are not included in the present analysis.

Spasojević (2026) examined the use of web analytics in optimizing email marketing campaigns at VVV Digital d.o.o. The analysis was based on internal campaign data covering the period from June 2025 to January 2026, during which 10,910 emails were sent to potential business partners. The study examined response patterns, content characteristics, and the importance of follow-up communication with recipients.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

Koščak (2026) analyzed the performance of online sales and various digital sales and marketing activities. The data enable comparisons among conventional online sales, kiosks, social media activities, free delivery, and a loyalty program, as well as their associations with sales and revenue indicators.

The relevance of the individual studies to the DAEP components is summarized in Table 3.

Table 3. Mapping of the Empirical Studies onto the Components of the DAEP Framework

Study	D – Digital Interaction & Data	A – Analytics & Decision-Making	E – Experience & Engagement	P – Performance
Starman (2026)	Online stores, user behavior	Monitoring UX and online performance indicators	Navigation, search functionality, product presentation, personalization, mobile experience	Conversion rate, bounce rate, shopping cart abandonment
Frlan (2026)	Online presence, digital channels	Web analytics and survey data	Functionality, visual design, communication	Behavioral and online performance indicators
Spasojević (2026)	Email campaigns and recipient responses	Analysis of responses, content, and follow-up contacts	Communication content and follow-up	Campaign response rates
Koščak (2026)	Online sales, kiosks, social media, loyalty program	Comparison of sales and business data	Engagement through different digital activities	Online sales, transactions, revenue

The results confirm the methodological heterogeneity of the cases while simultaneously enabling comparison of the key transitions within the DAEP framework.

D → A Transition: From Digital Interactions to Analytical Insights

Across all four studies, digital activities generate data that can be used to monitor and evaluate outcomes. The main differences among the cases concern the type of data generated and the way in which these data are used.

In Starman (2026), digital data are related to user behavior in online stores and indicators such as conversion rates, bounce rates, and shopping cart abandonment. The analytical use of these indicators enables comparison of performance before and after changes to specific elements of the user experience.

Frlan (2026) combines two data sources: web analytics and user survey data. This combination enables the simultaneous examination of digital indicators and user perceptions. However, because several changes were implemented concurrently, the observed outcomes cannot be attributed to any single intervention.

In Spasojević (2026), the empirical basis consists of internal email campaign data. The analysis of 10,910 sent emails enables the comparison of recipient responses according to communication characteristics and follow-up activities. The findings indicate that campaign data can be used to identify response patterns and formulate recommendations for further optimization.

Koščak (2026) uses sales and business data to compare the outcomes of different digital activities and channels. Such comparisons make it possible to distinguish between the level of digital activity and its actual contribution to sales or revenue outcomes.

A common pattern across the cases is therefore that digital interactions generate measurable data, but the analytical value of these data emerges only when they are compared and interpreted in relation to specific outcomes.

A → E Transition: From Analytical Insights to Changes in Digital Experience and Activities

Evidence for the **A → E** transition is most pronounced in the studies by Starman (2026), Frlan (2026), and Spasojević (2026).

In Starman (2026), analytical findings are linked to elements of the online user experience, including navigation, search functionality, information presentation, personalization, and mobile optimization. Across the cases examined, changes to specific UX elements were monitored using digital performance indicators, enabling an assessment of the outcomes associated with the implemented adjustments.

In Frlan (2026), the changes involved several elements of the firm's online presence, including visual and functional characteristics as well as digital communication. Web analytics and survey data enable the outcomes of the redesign to be monitored; however, because several interventions were implemented simultaneously, it is not possible to determine which individual element contributed to a specific change in the observed outcomes.

Spasojević (2026) identifies differences in response rates according to the characteristics of email communication and follow-up contact with potential business partners. The results indicate that different message content characteristics were associated with differences in response patterns, while systematic follow-up contact was associated with a higher number of responses. Based on these findings, recommendations were formulated for adapting future campaigns.

In Koščak (2026), the **A → E** transition is represented less directly, as the study focuses primarily on comparing the outcomes of digital activities that had already been implemented rather than on monitoring analytically informed changes in user experience.

E → P Transition: User Experience, Engagement, and Measurable Outcomes

The most direct evidence regarding the relationship between changes in user experience and measurable digital

or behavioral outcomes is provided by Starman (2026).

For the OneDrone online store, the conversion rate increased by 10% following an improvement in search functionality. At SWY, a bounce rate of 35% was recorded, while shopping cart abandonment decreased by 29%. At SnowMonkey, a 10% increase in conversion was recorded. At Pharmagea, conversion increased by 25%, while the bounce rate decreased by 20%. At Vezenina, the bounce rate was 28%, while shopping cart abandonment decreased by 30% (Starman, 2026).

These results indicate a temporal or substantive association between changes in UX elements and digital and behavioral indicators. Because the original study was not based on an experimental design, these differences cannot be interpreted as isolated causal effects of individual changes.

In Frlan (2026), positive changes were observed across several monitored indicators following the redesign of the firm's online presence and digital activities. Because the visual redesign, functional changes, and marketing activities were implemented simultaneously, the results support an association between the comprehensive digital redesign and changes in behavioral or online indicators, but do not allow the effect of any individual intervention to be identified.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

In Spasojević (2026), the relationship between the E and P components is reflected primarily in recipients' responses to email communication. Differences in message content and follow-up communication were accompanied by differences in responses from potential business partners; however, the study does not allow these outcomes to be directly linked to ultimate financial indicators.

Overall, the results provide more direct evidence at the **P_D and P_C** levels than at the **P_B** level.

Digital Activity and Business Value

Koščak (2026) provides particularly important findings for distinguishing between digital activity and business performance.

Online sales increased from approximately EUR 3.9 million in 2021 to EUR 4.7 million in 2024, representing growth of 20.51%. Although this growth was positive, it did not reach the 30% increase anticipated in the original study.

The results also did not support the expectation that free delivery would increase online sales by at least 10%. During periods in which free delivery was offered, revenues were in fact lower than in comparable periods without this activity.

Sales generated through kiosks amounted to approximately EUR 96,000 in 2024, representing 1.71% of total online sales, whereas the conventional website accounted for 98.29% of online sales. Activities on Facebook and Instagram also generated less than 1% of the firm's total annual revenue, which was below the minimum of 3% anticipated in the original study.

A different pattern was observed for the loyalty program. Members of the program generated 25.22% of total online revenue and accounted for 18.22% of online transactions (Koščak, 2026).

These results demonstrate that different digital activities are not associated with the same level of business outcomes. The presence or implementation of a digital activity therefore does not, in itself, provide sufficient grounds for conclusions about its contribution to business performance.

Results Across DAEP Performance Levels

The comparison of the four studies reveals differences in the representation of the three performance levels.

At the **P_D – Digital Performance** level, the evidence is most extensive. This level includes bounce rates, email response rates, shopping cart abandonment, use of digital channels, and other immediate indicators of digital interactions.

At the **P_C – Customer Performance** level, the findings are primarily related to conversion, user responses, purchasing behavior, repeated interactions, and loyalty. This level is particularly evident in Starman (2026), Spasojević (2026), and the loyalty program findings reported by Koščak (2026).

At the **P_B – Business Performance** level, the most direct evidence is provided by Koščak (2026), whose study analyzes revenue, online sales, and transactions. In the other studies, the relationship with ultimate financial outcomes is less direct, or the effect of an individual digital activity cannot be isolated.

The empirical evidence is therefore stronger for the relationships among digital activities, analytics, user experience, and immediate digital or behavioral outcomes than for the complete sequence leading to ultimate business or financial outcomes.

Empirical Support for the Research Propositions

Based on the structured comparison of all four cases, the empirical support for propositions P1–P6 was assessed. The results are summarized in Table 4.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

Table 4. Assessment of Empirical Support for the DAEP Research Propositions

Proposition	Assessment	Key Empirical Evidence
P1	**Supported**	Across all cases, data generated through digital interactions enable the analysis of outcomes; their usefulness is associated with their interpretation and application in decision-making.
P2	**Supported**	Starman, Frlan, and Spasojević provide evidence linking analytical findings to changes in UX, online presence, or communication activities.
P3	**Supported**	Changes in UX and communication elements are accompanied by changes in conversion rates, bounce rates, shopping cart abandonment, or response rates; however, the research designs do not allow for the isolated assessment of causal effects.
P4	**Partially supported**	Associations are observed among experience, behavioral responses, and certain business outcomes; however, the complete indirect pathway **E → P_C → P_B** is not directly examined across all cases.
P5	**Supported**	Koščak's findings indicate that individual digital activities do not necessarily generate the expected revenue effects despite their implementation or reach; this is particularly evident for free delivery, kiosks, and social media activities.
P6	**Partially supported**	In several cases, results are used to formulate recommendations and guide further optimization; however, the continuous **P → A** feedback loop was not directly monitored longitudinally.

The strongest empirical support was identified for propositions **P1, P2, and P5**. For P3, the findings are consistent with the proposed relationship; however, the methodological designs of the original studies do not allow causal relationships to be established. P4 and P6 have a weaker empirical basis, as the included studies do not systematically trace either the complete indirect process from user experience through behavioral outcomes to financial performance or the continuous feedback loop.

The overall result of the cross-case analysis therefore indicates **uneven empirical support across the individual transitions of the DAEP framework**. The clearest evidence concerns the transformation of digital data into analytically useful information, the use of analytical findings to adapt digital activities, and the distinction between digital activity and business outcomes. Relationships requiring the observation of multiple consecutive stages of value creation over a longer period are supported less directly.

DISCUSSION

The aim of this study was to develop the integrated DAEP conceptual framework and, through a structured cross-case analysis of four empirical studies, assess the support for its key components and process relationships. The findings indicate that digital activities do not, in themselves, constitute business value. Rather, their potential is realized through a sequence of processes in which data are transformed into analytical insights, analytical insights into organizational decisions and changes in digital experience, and user responses into different levels of performance. At the same time, the analysis demonstrates that empirical support is not equally strong across all transitions, which is important both for interpreting the framework and for identifying directions for its further empirical testing.

Digital Data Represent Potential, Not Business Value

The first important finding concerns the **D → A** transition. Across all analyzed cases, digital interactions generate data; however, their business relevance becomes apparent only through analysis, interpretation, and

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

linkage to specific outcomes. This finding supports the distinction between a firm's digital presence or activity and its digital capability.

This distinction is consistent with Järvinen and Karjaluoto (2015), who emphasize that web analytics is not merely a technical system for collecting metrics, but requires their integration with marketing objectives and organizational decision-making. Similarly, Brynjolfsson et al. (2011) emphasize the importance of the systematic use of data in decision-making.

The findings of the present study extend this argument through the process logic of the DAEP framework. Within the framework, digital activity represents a **source of data potential**, rather than an end result. A firm may be highly active in digital environments and generate large volumes of data, yet without adequate analytical capability, the **D → A** transition remains incomplete. Business value therefore depends not merely on the volume of digital activity, but on the organization's ability to transform data into knowledge relevant to decision-making.

Analytics Creates Value Through Organizational Response

The second finding concerns the **A → E** transition. The cross-case analysis indicates that analytical insight alone does not create user or business value. What is critical is the firm's ability to use the information obtained to modify its activities, digital touchpoints, or communication with customers.

This interpretation is consistent with Agag et al. (2024), whose findings indicate that the relationship between marketing analytics and customer satisfaction is associated with a firm's capability to respond to customer needs. Analytical capability therefore acquires business relevance only when combined with the organizational capability to act.

This interpretation is also consistent with research emphasizing the role of knowledge sharing in translating organizational knowledge into innovation outcomes (Rahman et al., 2025). From the DAEP perspective, this reinforces the argument that analytical knowledge acquires value only when it is transferred into organizational action.

DAEP conceptualizes this relationship as a distinct transition between **analytical insight and implementation response**. This distinction is important because it helps explain situations in which a firm possesses advanced analytical tools and high-quality data but fails to translate the resulting insights into improvements in user experience, communication, or other digital activities. In such cases, the limitation lies not at the level of data or analytics, but in the transformation of analytical knowledge into organizational action.

The findings therefore support P2 and indicate that analytical capability should be considered together with the firm's **responsive or implementation capability**.

Importantly, the A → E transition should not be understood as automatic. Its effectiveness may depend on organizational enabling conditions, including data literacy, cross-functional collaboration, technological maturity, knowledge-sharing practices, and the availability of implementation resources. These factors can facilitate or constrain the translation of analytical insights into changes in digital experience and should therefore be considered contextual moderators of the DAEP transitions rather than additional stages of the framework.

User Experience and Engagement as Linking Mechanisms

The third finding concerns the **E → P** transition. The analyzed cases indicate that changes in user experience and digital communication are associated with changes in digital and behavioral indicators. The most direct evidence concerns conversion rates, bounce rates, shopping cart abandonment, and responses to communication.

This finding is consistent with the conceptualization of user experience as a multidimensional outcome of users' interactions with digital touchpoints (Bleier et al., 2019; Rose et al., 2012). Lemon and Verhoef (2016)

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

further emphasize that experience develops throughout the entire customer journey, meaning that individual digital touchpoints should not be considered in isolation.

The DAEP framework positions user experience and engagement between organizational decision-making and measurable outcomes. Their role is therefore primarily **transformational or linking**: an analytically informed decision must be translated into a change that users can perceive and to which they can respond.

At the same time, the findings do not support the claim that an individual improvement in user experience directly causes a business outcome. Most of the original studies were not based on experimental or longitudinal designs that would allow individual effects to be isolated. P3 is therefore supported at the level of empirical consistency between changes in experience and behavioral responses, rather than as an established causal relationship.

From Customer Response to Business Value

The findings enable a distinction to be made among immediate digital outcomes, behavioral and relational customer-level outcomes, and business or financial outcomes. This distinction is particularly important for P4, which proposes that customer-level outcomes represent an intermediate stage between user experience and business performance.

This process logic is consistent with Mittal et al. (2023), whose meta-analytic synthesis links customer satisfaction and loyalty behaviors to firms' financial performance while also demonstrating that relationships with firm-level outcomes are more distal. Katsikeas et al. (2016) similarly emphasize the need to distinguish carefully among different categories of marketing performance.

The present analysis provides stronger support for the relationships between user experience and immediate digital or behavioral outcomes than for the complete sequence from experience through customer behavior to financial performance. P4 is therefore only partially supported.

This limitation is theoretically important. The DAEP framework does not assume that every positive change in user experience is necessarily translated into a financial outcome. Additional factors may operate between P_C – Customer Performance and P_B – Business Performance, which were not systematically examined in the present study. More broadly, research on organizational performance indicates that the effects of organizational capabilities may operate through intermediate mechanisms rather than directly (Ardabili et al., 2025), which is consistent with the process-oriented logic underlying the DAEP framework. The complete E → P_C → P_B pathway therefore represents one of the key areas for future empirical testing of the framework.

A further consideration is the temporal dimension of this transition. Changes in user experience or customer engagement may affect immediate digital indicators relatively quickly, whereas their effects on repeat purchasing, retention, revenue, or profitability may emerge only after a considerable time lag. The E → P transition should therefore not be interpreted as temporally immediate, and future empirical applications of DAEP should explicitly account for delayed effects across P_D, P_C, and P_B.

Digital Activity Is Not Equivalent to Business Performance

One of the clearest findings of the cross-case analysis is the support for P5. The results indicate that the existence of a digital channel, the implementation of a digital activity, or the achievement of an immediate digital response does not guarantee a proportional business effect. In some of the cases analyzed, digital activities did not achieve the expected sales or revenue outcomes, whereas other activities demonstrated substantially stronger associations with business results.

This finding reinforces the need to clearly distinguish among three levels of performance:

- **P_D – Digital Performance**;

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

- **P_C – Customer Performance**;
- **P_B – Business Performance**.

This distinction is consistent with Katsikeas et al. (2016), who highlight the heterogeneity of marketing performance indicators and the need to define performance outcomes precisely. Similarly, Järvinen and Karjaluoto (2015) emphasize that digital metrics need to be linked to actual marketing and business objectives.

For managerial decision-making, this means that increases in website traffic, clicks, reach, or other digital metrics do not constitute sufficient evidence of performance unless the firm understands how these outcomes relate to customer behavior and business effects. The DAEP framework therefore enables analysis not only of **whether a digital activity is successful**, but also of **the level at which it is successful and whether its effect is transferred to the next stage of value creation**.

Theoretical Contribution of the DAEP Framework

The theoretical contribution of this study does not lie in introducing entirely new individual constructs. Digital interactions, analytics, data-driven decision-making, user experience, customer engagement, and business performance are already established fields of research (Cioppi et al., 2023; Kannan & Li, 2017). The contribution of DAEP lies in their **process-oriented integration** and in the explicit conceptualization of the transitions through which digital potential may be transformed into business value.

On this basis, three central theoretical contributions can be identified.

First, DAEP integrates fragmented levels of digital value creation into a unified process-oriented framework. The framework connects the generation of digital data, their analytical processing, organizational action, user experience, behavioral responses, and business outcomes. In doing so, it enables the organizational and customer perspectives of digital business to be considered simultaneously.

Second, DAEP shifts analytical attention from the individual components to the transitions between them. The **D → A, A → E, E → P, and P → A** transitions enable the identification of points at which the value creation process may be strengthened, weakened, or disrupted. A firm may possess data without adequate analytics, analytics without organizational response, or strong digital metrics without corresponding business effects. The value of the framework therefore also lies in its ability to conceptualize **breakdowns in the transformation of digital potential into business outcomes**.

Third, DAEP introduces an explicit multilevel understanding of performance. Distinguishing among **P_D, P_C, and P_B** reduces the risk of equating digital activity with behavioral or financial outcomes and enables a more precise analysis of the value creation pathway.

In addition, the framework incorporates the **P → A** feedback relationship, meaning that digital value creation is not conceptualized as a one-time linear sequence. Outcomes become new data inputs for subsequent analysis and adaptation. In the present empirical analysis, this relationship is only partially supported and therefore represents an important theoretical extension requiring further longitudinal assessment.

Accordingly, DAEP represents a core process architecture of digital business value creation, while the effectiveness of individual transitions may vary according to organizational capabilities, contextual conditions, temporal dynamics, and the observability of customer interactions.

DAEP should therefore be understood as a theoretically derived and preliminarily empirically evaluated integrative conceptual framework, rather than as an already validated causal model.

Managerial Implications

The findings have several direct implications for digital business management. First, organizations need to shift from merely collecting digital metrics toward their systematic use in decision-making. Organizations

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

should not evaluate the success of digital activities solely on the basis of reach, visits, clicks, or other immediate indicators, but should determine how these metrics relate to customer behavior and business objectives.

Second, the findings highlight the need to organizationally integrate analytics and implementation. Analytical systems create value only when processes, responsibilities, and capabilities are in place to translate insights into concrete changes in user experience, communication, personalization, or other digital activities.

Third, the findings emphasize the need for multilevel performance measurement. For each digital activity, firms can define related indicators at the **P_D, P_C, and P_B** levels. Such an approach makes it possible to determine whether an improvement in an immediate digital metric is actually translated into a behavioral customer response and subsequently into a business outcome.

Fourth, the feedback logic of DAEP implies that performance measurement should not represent the endpoint of a digital activity, but rather an input into the next cycle of analysis, decision-making, and optimization. In this way, digital management can move from the occasional monitoring of indicators toward a more iterative process of organizational learning.

Fifth, the transition-oriented structure of DAEP provides a basis for the future development of a DAEP friction audit through which organizations could systematically identify bottlenecks at individual transition points. Potential transition indicators could include data quality and usability for D → A, the proportion of analytical insights translated into implemented actions for A → E, and the extent to which improvements in digital or customer-level outcomes are reflected in business outcomes for E → P. At this stage, such indicators should be regarded as a basis for future diagnostic tool development rather than as an empirically validated scorecard.

Research Limitations and Directions for Future Research

Several limitations should be considered when interpreting the findings. The first arises from the secondary nature of the analysis. The original studies were not designed to directly test the DAEP framework; therefore, the individual components and transitions are not equally represented across all cases.

The second limitation concerns the methodological heterogeneity of the studies. They differ in terms of research methods, data sources, sample sizes, time periods, business contexts, and indicators used. This heterogeneity enables a conceptual comparison across different digital environments, but limits the direct comparability of the findings and precludes the estimation of pooled effect sizes.

The third limitation concerns causality. Most of the analyzed studies do not employ experimental or longitudinal designs that would allow the effects of individual digital interventions to be isolated. The findings should therefore primarily be interpreted as indicating empirical consistency with individual relationships proposed by the framework, rather than as evidence of causal mechanisms.

The fourth limitation concerns the purposive selection of cases. The four studies provide conceptual diversity but do not constitute a statistically representative sample of firms, industries, or digital business practices. Generalization of the findings should therefore be **analytical or theoretical rather than statistical**.

A fifth limitation concerns the analytical representation of the digital value-creation process. The DAEP sequence is an analytical simplification of digital value creation rather than a representation of a strictly linear customer journey. Contemporary customer journeys may span multiple devices, platforms, digital and offline touchpoints, and interactions that cannot always be reliably attributed to a single channel. Consequently, empirical applications of DAEP should account for omnichannel attribution problems and incomplete observability of customer interactions across stages.

A sixth limitation concerns potential selection and context bias. Although the analysis explicitly retained negative and deviant findings, the purposive selection of four available studies may not capture the full range of failed, discontinued, or stalled digital initiatives that occur in practice. Future research should therefore

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue IX September 2026

deliberately include unsuccessful digital transformation and optimization cases to examine where and why individual DAEP transitions break down.

Future research should test the DAEP framework using research designs specifically developed to measure all four components and the transitions between them. Longitudinal studies are particularly important, as they would enable the **D → A → E → P → A** sequence to be observed over time.

Quantitative testing of the framework could employ **structural equation modeling (SEM or PLS-SEM)** to examine direct and indirect relationships among analytical capabilities, user experience, customer behavioral outcomes, and business performance. Experimental and quasi-experimental designs, including controlled A/B testing, could complement such analyses by isolating the effects of specific changes in user experience or digital communication on immediate behavioral outcomes. Combining longitudinal, experimental, and structural modeling approaches would provide stronger evidence regarding both individual DAEP transitions and the complete value-creation sequence. Of particular importance would be the empirical examination of P4, specifically the mediating role of **P_C** between user experience and **P_B**, as well as P6, which proposes the continuous reintegration of outcomes into the analytical process.

Future applications of the DAEP framework should also consider the increasing constraints on digital data collection arising from privacy regulation, platform-level tracking restrictions, and reduced cross-channel observability. Such developments may affect both the completeness of the D component and the reliability of subsequent analytical interpretation and therefore warrant explicit consideration in future empirical applications of the framework.

Future research may also examine how AI-enabled and generative AI systems alter the speed and degree of automation of DAEP transitions, particularly the transformation of data into analytical insights (D → A) and the translation of insights into personalized digital experiences (A → E).

Future research could also examine the moderating roles of **firm digital maturity, firm size, industry, competitive intensity, and market turbulence**. The effectiveness of individual DAEP transitions may not be universal, but may instead depend on the organizational and market context.

At its current stage of development, the DAEP framework should therefore be regarded as a foundation for further theoretical refinement and purpose-designed empirical testing rather than as a definitively validated model of digital business performance.

CONCLUSION

The aim of this study was to develop the integrated **Digital–Analytics–Experience–Performance (DAEP) conceptual framework** and, through a structured cross-case analysis of four empirical studies, assess the support for its key components and process relationships. The framework is based on the premise that digital activities and data do not, in themselves, create business value. Rather, business value emerges through a process in which digital data are transformed into analytical insights and decisions, these insights and decisions into changes in user experience and customer engagement, and user responses into different levels of measurable performance.

The findings provide answers to the research questions formulated in this study. With regard to **RQ1**, the analysis indicates that improved online business performance is associated not merely with the presence of digital channels, but primarily with the capability to systematically collect, interpret, and use data in decision-making. Regarding **RQ2**, the findings suggest that user experience represents an important linking mechanism between firms' digital activities and users' behavioral and relational responses, although the available evidence does not allow direct causal relationships to be established. In relation to **RQ3**, the findings confirm the role of web analytics and data-driven decision-making in identifying patterns, evaluating outcomes, and providing a basis for the optimization of digital activities. Regarding **RQ4**, the cross-case analysis demonstrates that different digital activities are not equally associated with business outcomes and that a high level of digital activity alone does not guarantee corresponding revenue or financial effects.

On this basis, the DAEP framework conceptualizes digital business value creation as a **D → A → E → P** process, with performance differentiated into **P_D – Digital Performance, P_C – Customer Performance, and P_B – Business Performance**. A particular contribution of the framework lies in its focus on the transitions between these components. These transitions make it possible to identify points at which the transformation of digital potential into business value may be strengthened, weakened, or disrupted. A firm may therefore possess digital data without using them effectively for analytical purposes, generate analytical insights without an adequate organizational response, or achieve favorable digital metrics without a comparable business effect.

The cross-case analysis provides the clearest support for the importance of analytically interpreting digital data, translating analytical findings into concrete digital activities, and distinguishing between digital activity and actual business performance. Less direct support was found for the complete sequence from user experience through behavioral outcomes to financial performance and for the continuous feedback loop through which achieved outcomes are systematically reintegrated into the analytical process.

The theoretical contribution of the study therefore lies primarily in the **process-oriented integration of areas that have otherwise largely been examined separately, including digital interactions, analytics, user experience, customer engagement, and business performance**, in its emphasis on the transitions between individual stages, and in its multilevel differentiation of performance outcomes. At the same time, the framework provides a practical basis for assessing whether a firm merely generates and monitors digital data or actually transforms them into decisions, improvements in user experience, and measurable business value.

At its current stage of development, DAEP should be understood as a **theoretically derived integrative conceptual framework that has been preliminarily evaluated across several heterogeneous empirical cases**, rather than as a definitively validated causal model. Future research should examine its proposed relationships using purpose-designed longitudinal and quantitative research designs, particularly the complete **E → P_C → P_B** pathway and the **P → A** feedback loop.

The central conclusion of the study is that digital business value does not arise from a firm's mere presence in the digital environment or from the volume of data it generates, but from its capability to **integrate data, analytics, decision-making, user experience, and outcomes into a continuous process of value creation**.

REFERENCES

1. Agag, G., Shehawy, Y. M., Almoraish, A., Eid, R., Chaib Lababdi, H., Gherissi Labben, T., & Abdo, S. S. (2024). Understanding the relationship between marketing analytics, customer agility, and customer satisfaction: A longitudinal perspective. Journal of Retailing and Consumer Services, 77, 103663. https://doi.org/10.1016/j.jretconser.2023.103663
2. Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness. Journal of Retailing, 91(1), 34–49. https://doi.org/10.1016/j.jretai.2014.09.005
3. Alves Gomes, M., & Meisen, T. (2023). A review on customer segmentation methods for personalized customer targeting in e-commerce use cases. Information Systems and e-Business Management, 21(3), 527–570. https://doi.org/10.1007/s10257-023-00640-4
4. Ardabili, F. S., Verbenko, G., & Cajnko, P. (2025). The effects of organizational agility on organizational performance: The mediating role of ambidexterity. RISUS – Journal on Innovation and Sustainability, 16(2), 114–123. https://doi.org/10.23925/2179-3565.2025v16i2p114-123
5. Bleier, A., Harmeling, C. M., & Palmatier, R. W. (2019). Creating effective online customer experiences. Journal of Marketing, 83(2), 98–119. https://doi.org/10.1177/0022242918809930
6. Blut, M., Kulikovskaja, V., Hubert, M., Brock, C., & Backhaus, C. (2023). Effectiveness of engagement initiatives across engagement platforms: A meta-analysis. Journal of the Academy of Marketing Science, 51, 941–965. https://doi.org/10.1007/s11747-023-00925-7
7. Brodie, R. J., Ilic, A., Juric, B., & Hollebeek, L. (2013). Consumer engagement in a virtual brand community: An exploratory analysis. Journal of Business Research, 66(1), 105–114. https://doi.org/10.1016/j.jbusres.2011.07.029

8. Brynjolfsson, E., Hitt, L. M., & Kim, H. H. (2011). Strength in numbers: How does data-driven decisionmaking affect firm performance? SSRN. https://doi.org/10.2139/ssrn.1819486
9. Calderon-Monge, E., & Ribeiro-Soriano, D. (2024). The role of digitalization in business and management: A systematic literature review. Review of Managerial Science, 18, 449–491. https://doi.org/10.1007/s11846-023-00647-8
10. Cioppi, M., Curina, I., Francioni, B., & Savelli, E. (2023). Digital transformation and marketing: A systematic and thematic literature review. Italian Journal of Marketing, 2023, 207–288. https://doi.org/10.1007/s43039-023-00067-2
11. Eisenhardt, K. M. (1989). Building theories from case study research. Academy of Management Review, 14(4), 532–550. https://doi.org/10.2307/258557
12. Eisenhardt, K. M., & Graebner, M. E. (2007). Theory building from cases: Opportunities and challenges. Academy of Management Journal, 50(1), 25–32. https://doi.org/10.5465/amj.2007.24160888
13. Ellis-Chadwick, F., & Doherty, N. F. (2012). Web advertising: The role of e-mail marketing. Journal of Business Research, 65(6), 843–848. https://doi.org/10.1016/j.jbusres.2011.01.005
14. Frlan, P. (2026). Prenova spletne prisotnosti in trženjskih strategij kot orodje za rast prodaje: Študija primera Sivka Zdravo Življenje d.o.o. [Unpublished diploma thesis in preparation]. GEA College – Center višjih šol.
15. Hanelt, A., Bohnsack, R., Marz, D., & Antunes Marante, C. (2021). A systematic review of the literature on digital transformation: Insights and implications for strategy and organizational change. Journal of Management Studies, 58(5), 1159–1197. https://doi.org/10.1111/joms.12639
16. Heaton, J. (2008). Secondary analysis of qualitative data: An overview. Historical Social Research / Historische Sozialforschung, 33(3), 33–45. https://www.jstor.org/stable/20762299
17. Homburg, C., Jozić, D., & Kuehnl, C. (2017). Customer experience management: Toward implementing an evolving marketing concept. Journal of the Academy of Marketing Science, 45, 377–401. https://doi.org/10.1007/s11747-015-0460-7
18. Järvinen, J., & Karjaluoto, H. (2015). The use of Web analytics for digital marketing performance measurement. Industrial Marketing Management, 50, 117–127. https://doi.org/10.1016/j.indmarman.2015.04.009
19. Kannan, P. K., & Li, H. "A." (2017). Digital marketing: A framework, review and research agenda. International Journal of Research in Marketing, 34(1), 22–45. https://doi.org/10.1016/j.ijresmar.2016.11.006
20. Katsikeas, C. S., Morgan, N. A., Leonidou, L. C., & Hult, G. T. M. (2016). Assessing performance outcomes in marketing. Journal of Marketing, 80(2), 1–20. https://doi.org/10.1509/jm.15.0287
21. Koščak, B. (2026). Dejavniki uspešne spletne prodaje na primeru večjega trgovskega podjetja s športno opremo [Unpublished final thesis submitted for defense]. GEA College – Center višjih šol.
22. Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. Journal of Marketing, 80(6), 69–96. https://doi.org/10.1509/jm.15.0420
23. Mehrabi, H., Chen, Y. K., & Keramati, A. (2024). Developing customer analytics capability in firms of different ages: Examining the complementarity of outside-in and inside-out resources. Industrial Marketing Management, 118, 145–159. https://doi.org/10.1016/j.indmarman.2024.02.009
24. Mittal, V., Han, K., Frennea, C., Borges, A., & Sridhar, S. (2023). Customer satisfaction, loyalty behaviors, and firm financial performance: What 40 years of research tells us. Marketing Letters, 34, 171–187. https://doi.org/10.1007/s11002-023-09671-w
25. Norman, D. A. (2013). The design of everyday things (Rev. and expanded ed.). Basic Books.
26. Rahman, M. M., Röntynen, R., Ardabili, F. S., Newaz, H. T. M. Q., Voitenko, E., & Cajnko, P. (2025). Knowledge leadership and innovation: The mediating role of knowledge sharing. Journal of Ecohumanism, 4(2), 249–260. https://doi.org/10.62754/joe.v4i2.5933
27. Rose, S., Clark, M., Samouel, P., & Hair, N. (2012). Online customer experience in e-retailing: An empirical model of antecedents and outcomes. Journal of Retailing, 88(2), 308–322. https://doi.org/10.1016/j.jretai.2012.03.001
28. Ruggiano, N., & Perry, T. E. (2019). Conducting secondary analysis of qualitative data: Should we, can we, and how? Qualitative Social Work, 18(1), 81–97. https://doi.org/10.1177/1473325017700701

29. Spasojević, T. (2026). Vloga spletne analitike pri optimizaciji e-mail marketing kampanj v izbranem podjetju [Unpublished final thesis submitted for defense]. GEA College – Center višjih šol.
30. Starman, P. (2026). Vpliv ključnih elementov uporabniške izkušnje na prodajno uspešnost spletnih trgovin v različnih panogah [Diploma thesis]. GEA College – Center višjih šol.
31. Weidig, J., Weippert, M., & Kuehnl, C. (2024). Personalized touchpoints and customer experience: A conceptual synthesis. Journal of Business Research, 177, 114641. https://doi.org/10.1016/j.jbusres.2024.114641
32. Yin, R. K. (2018). Case study research and applications: Design and methods (6th ed.). SAGE Publications.