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Odnos inženjerske percepcije uspešnosti razvoja dizajna proizvoda i marketinga zasnovanog na podacima

Tamara Panajotović¹, Klara Djurović², Marija Nikolić³, Iva Vojinović⁴, Tatjana Jovanović⁵

¹ School of Engineering Management, University "Union - Nikola Tesla" Belgrade, Serbia,
tamara.panajotovic@fim.rs, ORCID: 0000-0002-0863-3502

² Faculty of Economics and Business, Mediterranean University, Podgorica, Montenegro,
klaradjurovic5@gmail.com

³ Faculty of Economics and Business, Mediterranean University, Podgorica, Montenegro,
marijapopovic88@yahoo.com

⁴ Department of Psychology, University of London, United Kingdom, ivavojinovic1589@gmail.com

⁵ School of Engineering Management, University "Nikola Tesla" Belgrade Serbia, tatjana.jovanovic@fim.rs,
ORCID: 0000-0002-3400-3467

Apstrakt: Trenutno se nalazimo u procesu intenzivne digitalizacije, podaci koji generišu milioni predmeta koji nas okružuju stalno se povećavaju. Marketing zasnovan na podacima ima značajnu ulogu u procesu razvoja novih proizvoda, jer obezbeđuje relevantne informacije o ponašanju i preferencijama korisnika. Cilj ovog rada je da ispita povezanost između primene data-driven marketinga i percepcije uspešnosti razvoja dizajna proizvoda. Istraživanje je sprovedeno metodom anketiranja na uzorku inženjera zaposlenih u različitim industrijama. Rezultati istraživanja pokazuju statistički značajne razlike u svim dimenzijama percepcije uspešnosti razvoja dizajna proizvoda između inženjera koji koriste marketing zasnovan na podacima i onih koji ga ne koriste, pri čemu su više vrednosti na ovim dimenzijama zabeležene kod onih koji koriste ovaj pristup. Takođe, utvrđene su statistički značajne pozitivne korelacije između svih dimenzija percepcije uspešnosti razvoja dizajna proizvoda nivoa primene marketinga zasnovanog na podacima, i učestalosti korišćenja alata za analizu podataka. Dobijeni nalazi ukazuju na značaj integracije tržišnih podataka i analitike u proces razvoja proizvoda u savremenim organizacijama.

Ključne reči: data-driven marketing, tržište, dizajn proizvoda, inženjerski dizajn, razvoj proizvoda.

The Relationship Between Engineers' Perception of the Success of Product Design Development and Data-Driven Marketing

Abstract: In the context of accelerating digital transformation, the volume of data generated by interconnected devices, systems, and digital interactions continues to grow exponentially. Data-driven marketing has emerged as a critical component of contemporary product development processes, providing organizations with valuable insights into customer needs, preferences, and behavioral patterns. The aim of this study is to examine the relationship between the implementation of data-driven marketing practices and the perceived success of product design development. The research was conducted using a survey methodology on a sample of engineers employed across various industries. The findings reveal statistically significant differences across all dimensions of perceived product design development success between engineers who utilize data-driven marketing and those who do not, with higher evaluations consistently reported by respondents applying this approach. Furthermore, statistically significant positive correlations were identified between all dimensions of perceived product design development success, the level of data-driven marketing implementation, and the frequency of data analytics tool usage. These results underscore the strategic importance of integrating market intelligence and data analytics into product development activities and suggest that data-driven approaches may contribute to enhancing the effectiveness of product design processes in contemporary organizations.

Keywords: data-driven marketing, market, product design, engineering design, product development.

1. Introduction

The development of digital technologies and the availability of large amounts of data have enabled organizations to better understand consumer needs. In modern business conditions, product development represents one of the key factors of company competitiveness. According to Kotler and Keller (2016), modern marketing involves making decisions based on data and market analysis. The integration of this information into engineering design enables the development of products that are better aligned with market requirements (Brown & Katz, 2011; Ulrich & Eppinger, 2016). In addition, the concept of product development based on user feedback has been further popularized through the Lean approach, which emphasizes the importance of continuous testing and the use of data in decision-making (Ries, 2011; Blank, 2013). In this way, the risk of failure is reduced and the probability of market success of a product is increased (Cooper, 2019). Traditional approaches to product development, which largely rely on intuition and engineers' experience, are increasingly being replaced by data-driven approaches (Davenport & Harris, 2017). The development of digital technologies, large databases (Big Data), and advanced analytical tools has enabled companies to better understand consumer needs, preferences, and behavior (Chen et al., 2012; Wedel & Kannan, 2016). The development of data-driven technologies, and the democratization of data science, have facilitated the implementation of big data approaches across various engineering disciplines, including engineering design (Kusiak, 2018). When we talk about data-driven decision-making, we refer to the use of quantitative information, data collection methods, analytical models, and predictive algorithms in marketing, as well as data from social media and customer reviews (Shmueli & Koppius, 2011; Rust et al., 2020). Advances in machine learning, artificial intelligence, and cloud-based analytics have provided marketing professionals with real-time big data analysis and the ability to predict and respond to consumer demand (Jordan & Mitchell, 2015; Kumar et al., 2020).

In recent years, various aspects of data-driven approaches in engineering design have been studied (Verganti, 2017; Kusiak, 2019). However, there is currently no widely accepted definition of Data-Driven Engineering Design (DDED) due to the novelty of approaches that integrate data into engineering. Accordingly, several terms and frameworks have been proposed in the literature to address different aspects of the design and product development process. Van Horn and Olewnik (2012) introduced the term *design analytics* as a new paradigm for improving the transformation of design information into knowledge, based on the extensive use of large datasets on users and design. Liu and Chen (2016) define data-driven design in relation to the optimization of promotional campaigns.

Feng and Zhao (2020) described data-driven product design as a process of identifying relevant and hidden patterns through modeling and analysis of product-related data in order to support product design. Based on the product design process, they developed a research framework that includes customer requirements analysis, conceptual design, detailed design, and design knowledge support tools.

Thus, the literature indicates the importance of applying a data-driven approach in the design and product development process; however, existing studies are predominantly theoretically oriented and focused on the conceptual definition of this approach (Van Horn et al., 2012; Feng & Zhao, 2016). Empirical studies examining the practical application and effectiveness of data-driven approaches in real business environments, as well as their impact on decision quality and product development success, are still insufficiently represented. There is also a noticeable lack of integrated models that connect data analysis with all stages of the product development process, from identifying user needs to the final design. A particular research gap exists regarding the understanding of challenges and limitations in applying this approach in practice, especially in the context of data availability, technical capabilities, and organizational factors.

When discussing the advantages of the data-driven approach, its application in product design brings numerous benefits. First of all, it enables more informed and objective decision-making based on real data about users and the market. Such an approach contributes to a better understanding of user needs, identification of hidden patterns and trends, as well as optimization of the product development process.

However, the application of the data-driven approach also faces certain challenges and limitations. One of the key issues relates to the availability and quality of data, which can significantly affect the reliability of decisions made. Additionally, implementing this approach requires adequate technical infrastructure, as well as expertise in data analysis, which can represent a barrier for organizations with limited resources. Furthermore, overreliance on data can lead to the neglect of creativity and intuitive approaches in design. There are also challenges related to data interpretation, as well as potential ethical issues concerning the collection of user data. In the context of marketing, the application of a data-driven approach enables organizations to better understand consumer behavior and

preferences. By using data from various sources such as digital platforms, social networks, and customer relationship management systems, it is possible to create personalized marketing strategies and improve user experience. Data-driven marketing contributes to more precise market segmentation, more effective targeting, and optimization of promotional campaigns. It also enables real-time performance measurement, leading to faster decision-making and better management of marketing budgets.

When discussing the disadvantages of the data-driven approach in marketing, one of the key issues concerns privacy protection and the ethical use of consumer data, which has become particularly important in today's digital environment. Additionally, the quality and reliability of data can significantly influence the success of marketing decisions, while their incorrect interpretation may lead to inefficient or even counterproductive campaigns.

Moreover, excessive reliance on quantitative data can limit creativity in marketing and overlook the emotional and psychological aspects of consumer behavior. Taking into account the mentioned advantages and limitations of the data-driven approach in marketing, there is a clear need for empirical research on its application in the modern business environment.

This study aims to investigate the relationship between the implementation of data-driven marketing and perceptions of product design development success, with particular emphasis on the effectiveness of decision making and product development processes.

2. Research Methodology

2.1. Sample

The research was conducted on a convenient sample of 150 engineers employed in different industries. The sample included respondents from the food industry (N=45), information technology industry (N=40), electrotechnical industry (N=25), and pharmaceutical industry (N=24), while 16 respondents were employed in other industries. Regarding the sample structure, the research included 95 women (63,3%) and 55 men (36.7%), aged between 25 and 62 years (M=39.55; SD = 9.18). The average work experience in the engineering profession ranged from six months to 35 years (M=9.75; SD = 7.09). The respondents were contacted through personal and professional contacts and the questionnaire was distributed electronically. Participation in the research was voluntary and based on the informed consent of the respondents. Participants were recruited through professional networks, business contacts, and social media platforms. Data collection was carried out from January to April 2026.

Research variables

Dependent variable: The perception of product design development success encompassed four dimensions representing the author's operationalization of the construct, based on a review of the literature and professional expertise in the field.

- technical success
- market adequacy
- process success, and
- product design success

To operationalize the dependent variable, the product Design Development Success Perception Questionnaire (PDDSPQ) was developed.

Independent Variables: The variables associated with the implementation of data-driven marketing included:

- the use data-driven marketing (users vs. non-users),
- the level of data-driven marketing implementation (1= very low; 5 = very high), and
- the frequency of use of data analytics tools (0= never; 4 = always).

To operationalize the aforementioned independent variables, a set of questions was developed to capture the corresponding values.

Product Design Development Success Perception Questionnaire (PDDSPQ)

The Product Design Development Success Perception Questionnaire (PDDSPQ) consists of a total of 16 items divided into 4 subscales, covering each dimension with 4 items:

Technical success (example item: “The product operates reliably under intended conditions.”). Market adequacy (example item: “The product meets the needs of target users.”). Process success (example item: “The development proceeded in accordance with planned deadlines.”). Product design success (example item: “The product design enables simple and efficient use.”). Respondents are required to rate the statements in the questionnaire with respect to the last product development project in which they participated, using a five-point Likert-type self-assessment scale (1 = strongly disagree; 5 = strongly agree). Since the questionnaire was developed for the purposes of this research, its psychometric properties are presented below. Specifically, internal consistency reliability was assessed using Cronbach’s alpha coefficient, while construct validity was evaluated through confirmatory factor analysis (CFA).

Table 1. Reliability check of internal consistency (Cronbach’s alpha coefficient)

Subscales	α
Technical success	.92
Market adequacy	.88
Process success	.85
Product design success	.86
Entire scale	.96

Scoure: Author’s own calculation.

The results of the reliability analysis (Table 1) indicate that all four subscales, as well as the overall scale, demonstrated satisfactory reliability in the present sample. (Fajgelj, 2013).

Table 2. Results of confirmatory factor analysis (four-factor model)

Model	χ^2	Df	CFI	TLI	RMSEA (IC 90%)	SRMR
Basic model (4 factors)	292.53*	98	.902	.880	.115 (.100 .130)	.049
Model with correlated residuals	252.06*	96	.921	.902	.104 (.089 .120)	.049

Note: CI 90% – 90% confidence interval; $p < .001$

Source: Author’s own calculations.

The results of the construct validity assessment of the basic model showed that the chi-square test statistic is statistically significant, which does not support model fit. However, given that one of the limitations of the chi-square test is that it is often significant in large samples, attention was focused on other fit indices. The results of the original model indicated that the CFI and SRMR indices were within acceptable limits, while TLI and RMSEA were close to the threshold values (CFI and TLI $\geq .90$; RMSEA and SRMR $\leq .08$). Therefore, a model correction was performed by allowing correlations between residuals of items with the highest modification indices (items 3 and 14, and items 7 and 11). In this adjusted model, TLI became acceptable, while RMSEA remained at the borderline level. Overall, the findings suggest satisfactory construct validity of the questionnaire within the studied sample.

The obtained results of Cronbach’s alpha and confirmatory factor analysis support the reliability and construct validity of the questionnaire in this sample.

Research hypotheses

H1: The dimensions of perceived success in product design development (technical success / market adequacy / process success / product design success) are significantly higher among engineers who use data-driven marketing.

H2: The dimensions of perceived success in product design development (technical success / market adequacy / process success / product design success) are positively and significantly correlated with the level of application of data-driven marketing.

H3: The dimensions of perceived success in product design development (technical success / market adequacy / process success / product design success) are positively and significantly correlated with the frequency of use of data analysis tools.

Research procedure

The participants were recruited online using the Google Forms platform. The questionnaire link was distributed through professional networks, business contacts and social media platforms. Before completing the

questionnaire, respondents were informed about the purpose of the study, data anonymity, the method of data processing, and the exclusive use of the data for scientific research purposes. All participants provided informed consent prior to participation in the study.

Data Analysis

The data were processed using IBM SPSS Statistics (Version 26) and JASP software. The following descriptive statistics were used: frequency (N), percentage (%), minimum (Min), maximum (Max), arithmetic mean (M), standard deviation (SD), skewness, and kurtosis. To assess the reliability and validity of the Product Design Development Success Perception Questionnaire (PDDSPQ), Cronbach's alpha coefficient and confirmatory factor analysis (CFA) were used. The inferential statistical procedures employed in this study included Pearson's correlation coefficient and t-test.

3. Results

First, descriptive statistics for the dimensions of perceived product design development success are presented, together with the intercorrelations among these dimensions.

Table 3. Descriptive statistical measures and intercorrelations of dimensions of perceived success in product design development

	<i>Min</i>	<i>Max</i>	<i>M</i>	<i>SD</i>	<i>Sk</i>	<i>Ku</i>	1	2	3
1. Technical success	1.50	5.00	3.93	1.02	-0.83	-0.37	/		
2. Market adequacy	1.75	5.00	4.12	0.83	-0.88	0.03	.89**	/	
3. Process success	2.25	5.00	4.00	0.78	-0.48	-0.75	.76**	.78**	/
4. Product design success	1.60	4.00	3.28	0.60	-0.51	-0.57	.75**	.79**	.74**

Note. Min – minimum; Max – maximum; M – arithmetic mean; SD – standard deviation; Sk – skewness; Ku – kurtosis; ** statistically significant Pearson correlation ($p < .01$).

Source: Author's own calculations.

The data presented in Table 3 show that all variables are approximately normally distributed, as skewness and kurtosis values are within the range of ± 2 , which some authors consider acceptable for deviations from normal distribution (Hair et al., 2022). Therefore, parametric statistical techniques were used in further analyses. The results of Pearson correlation coefficients (Table 3) show that the dimensions of perceived success in product design development are positively and statistically significantly correlated with each other. This indicates that respondents who assign higher ratings to one dimension of success generally tend to assign higher ratings to the other performance dimensions as well.

To test the first research hypothesis, i.e., whether the success dimensions in product design development are significantly more pronounced among engineers who use data-driven marketing, t-tests were conducted, as presented in Table 4.

Table 4. Differences in dimensions of perceived success of product design development with respect to the use of data-driven marketing

	Category	<i>N</i>	<i>M</i>	<i>SD</i>	<i>t (df)</i>	<i>d</i>	<i>p</i>
Technical success	Use	99	4.37	0.61	7.55 (65.63)	1.55	<.001
	Does not use	51	3.09	1.13			
Market adequacy	Use	99	4.46	0.52	7.11 (66.39)	1.45	<.001
	Does not use	51	3.47	0.93			
Process success	Use	99	4.25	0.63	5.55 (80.36)	1.04	<.001
	Does not use	51	3.52	0.83			
Product design success	Use	99	3.48	0.46	5.88 (76.41)	1.13	<.001
	Does not use	51	2.88	0.65			

p-value < .001 for all comparisons. Note: t – t statistic; df – degrees of freedom; d – Cohen's d (effect size).

Source: Author's own calculations.

The results of the t-tests (Table 4) showed statistically significant differences across all four dimensions of perceived product design development success, depending on whether engineers use data-driven marketing or not. Specifically, the results indicate that these dimensions (technical success, market adequacy, process success, and product design success) are more pronounced among engineers who use data-driven marketing, and the effect size of these differences is large.

Next, in order to test the second and third hypotheses, i.e., to examine the relationship between perceived success in product design development and the level of application of data-driven marketing, as well as the frequency of use of data analysis tools, Pearson correlation coefficients were used, which are presented in Table 5.

Table 5. Correlations between dimensions of perceived success of product design development, the level of application of data-driven marketing, and the frequency of use of data analysis tools

	Level of application of data-driven marketing	Frequency of use of data analysis tools
Technical success	.68**	.54**
Market adequacy	.62**	.52**
Process success	.52**	.41**
Product design success	.58**	.46**

Note. ** statistically significant Pearson correlation ($p < .01$).

Source: Author's own calculations.

The results of the correlation analysis (Table 5) showed that there are statistically significant positive correlations between all dimensions of perceived success in product design development and the level of application of data-driven marketing, as well as between the dimensions of perceived success in product design development and the frequency of use of data analysis tools. Therefore, the results suggest that respondents who perceive a higher level of data-driven marketing implementation and more frequent utilization of data analytics tools tend to report higher levels of product design development success.

4. Discussion

The results of this study indicate the existence of statistically significant differences in the perceived success of product design development between engineers who use data-driven marketing and those who do not. Furthermore, positive relationships were identified between the level of implementation of data-driven marketing, the frequency of data analytics tool usage, and the perceived success of product design development. The findings suggest that respondents who employ data-driven marketing practices report higher evaluations of product development success. These results imply that participants recognize the importance of data utilization in decision-making processes, particularly in adapting product to market demands. Such findings may be explained by the growing need to integrate market information into the technical processes of product development.

The obtained findings are in line with previous research indicating that the integration of market data and analytics can contribute to more efficient decision-making in the product development process (Davenport & Harris, 2017; Wedel & Kannan, 2016). Additionally, the results support the views of authors who emphasize the importance of a data-driven approach in modern engineering design (Kusiak, 2018; Feng & Zhao, 2020). These results can be seen in the broader context of digital transformation and the development of Industry 4.0 approaches, within which data plays an increasingly important role in business decision-making. This aligns with the popular saying that sees data as the "new oil" and highlights the enormous value contained in information, which must be processed and utilized to drive progress and profitability. Modern technologies, including big data sets, artificial intelligence (AI), and the Internet of Things, enable more efficient data collection and analysis on a large scale, allowing business actors to make more precise, faster, and evidence-based decisions. Therefore, data-driven marketing represents a significant mechanism for connecting user needs with technical solutions, reducing uncertainty and increasing the likelihood of success for new products.

Several limitations of this study should be acknowledged. First, the sample was convenience-based and relatively small, which limits the generalizability of findings. In addition, respondents were drawn from different industries, which may further restrict the applicability of the results across specific industrial contexts. Furthermore, a new instrument development for the purposes of this study. Although its psychometric properties were satisfactory within the present sample, additional validation on larger and more diverse samples is required. The data were also collected through self-report measures, which may be influenced by socially desirable responses and subjective evaluations. Finally, due to the cross-sectional nature of the research design, causal relationships cannot be established.

Future studies should therefore employ larger and more representative samples, focus on specific industries, and further examine the psychometric properties of developed instrument. The application of experimental research designs is also recommended to provide more robust evidence regarding causal relationships.

Despite these limitations, the findings of this study offer several important practical implications. The results highlight the importance of developing data-driven capabilities within organizations. This involves not only the implementation of data analytics tools but also the education and training of employees, particularly engineers, to effectively utilize data in decision-making processes. In this regard, organizations may benefit from developing internal training programs that facilitate the integration of technical and market-related information throughout the product development process. Furthermore, the findings suggest that closer collaboration between marketing and engineering teams may play a crucial role in enhancing product development success. The use of customer and market data enables engineers to make more informed decisions, thereby reducing the risk of developing product that do not align with market needs.

From an organizational perspective, the results may also contribute to the design of product development strategies based on an interdisciplinary approach, in which decisions are informed not only by technical criteria but also by the analysis of market data. Finally, the developed instrument (PPSPDD – Product Perception of Successful Product Design Development Questionnaire) may have practical value as a tool for the internal evaluation of product development success and for identifying areas requiring improvement within organizations.

5. Conclusion

The results of this research indicate the importance of data-driven marketing in the process of developing and designing new products. The findings confirm that the application of a data-driven approach contributes to more successful decision-making across all analyzed dimensions of perceived success in product design development, including technical success, market adequacy, process success, and overall product design success.

The results showed statistically significant differences between engineers who use data-driven marketing and those who do not, with higher values recorded among respondents who apply this approach in their work. Positive correlations were also confirmed between the level of application of data-driven marketing, the frequency of using data analysis tools, and perceptions of product development success, thereby providing support for the research hypotheses.

The findings indicate that modern companies increasingly recognize the importance of integrating market information and analytics into technical product development processes. In conditions of accelerated digitalization and Industry 4.0 development, data represents an important strategic resource that enables better understanding of user needs, reduction of product failure risk, and increased competitive advantage.

The scientific contribution lies in linking data-driven marketing with engineering perceptions of product design development success, while the practical contribution highlights the importance of applying analytical tools and market data in the process of new product development in modern organizations.

Study limitations relate to sample size and structure, as well as the fact that data were collected via self-assessment. Future research could include a larger number of industries and longitudinal studies examining the impact of analytical tools and technologies on development success.

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