

# How important are behavioral analytics tools in the age of modern digital marketing?

Marian Olinski<sup>1</sup>, Kacper Siecinski<sup>2</sup>, Kuanchin Chen<sup>3</sup>

<sup>1</sup> University of Warmia and Mazury in Olsztyn, Faculty of Economic Sciences, Institute of Management and Quality Sciences, Poland, ORCID: 0000-0002-1707-0553, olinski@uwm.edu.pl (corresponding author);

<sup>2</sup> University of Warmia and Mazury in Olsztyn, Faculty of Economic Sciences, Institute of Management and Quality Sciences, Poland, ORCID: 0000-0001-8484-0741, kacper.siecinski@uwm.edu.pl;

<sup>3</sup> Western Michigan University, Department of Business Information Systems, United States of America, ORCID: 0000-0002-3518-4036, kc.chen@wmich.edu.

**Abstract:** This study evaluates how behavioral analytics tools contribute to short-term business objectives in digital marketing. We analyze 73 case studies from 12 brands collected on October 3, 2023, using content analysis to extract tools, outcomes, and problems addressed. Expert weighting from three senior scholars is applied to value outcome categories, with moderate agreement reported by Kendall's  $W = 0.47$ . We then compute aggregate tool evaluations, build a co-occurrence matrix, and estimate linear and multiple regressions together with Pearson correlations. Synergies with top-rated tools are strongly associated with more outcomes achieved, the total result increases by 2.8295 for each additional co-occurrence, with  $R^2 = 0.936$ , and the largest effect appears for conversion and site optimization. Tool ratings are highly correlated with the number of problems solved,  $r = 0.9888$ . Effectiveness in solving UX and optimization issues is strongly associated with gains in satisfaction and loyalty,  $r = 0.9646$ , with a positive regression coefficient for this category. Session recordings, heatmaps, A/B testing, and conversion funnels emerge as the most impactful instruments. We propose a six-category framework and provide practical guidance for integrating complementary tools within iterative, data-driven workflows. Results underline the strategic role of behavioral analytics in improving conversion, satisfaction, and short-term performance.

**Keywords:** Information management, behavioral analysis, user experience, digital technologies, heatmaps.

**JEL Classification:** D80, D91, L86.

**APA Style Citation:** Olinski, M., Siecinski, K., & Chen, K. (2026). How important are behavioral analytics tools in the age of modern digital marketing? *E&M Economics and Management*, 29(1), 183–206. <https://doi.org/10.15240/tul/001/2026-1-012>

## Introduction

Information technology and digital infrastructure have turned social networks from interpersonal tools into catalysts of brand and business growth, which makes analytics essential for effective strategies (Saeidi & Baradari, 2023). In the digital age, uncertainty in business processes and the ubiquity of digital content require advanced analytical tools rooted in AI and behavioral data sciences, as well as continuous monitoring of user behavior (Davidavičienė

et al., 2014; Saura et al., 2021). The COVID-19 pandemic accelerated digitization and shifted interactions online, expanding e-commerce and social selling, which strengthens the strategic need for behavioral analytics as shopping habits and peer opinions gain importance (Huang & Lin, 2022; Manchia et al., 2022; Miah et al., 2022).

Behavioral analytics supports decision making, enables precise performance measurement, and powers personalization and

segmentation that improve user experience, conversions, and loyalty, which helps firms remain competitive as preferences change rapidly (Alfian et al., 2019; Miklosik et al., 2019; Treboux et al., 2016; Wedel & Kannan, 2016). This study examines how specific tools and their configurations affect short-term business goals on websites and business profiles.

The study addresses the following research questions:

*RQ1: How effective are behavioral analytics tools in achieving short-term business goals?*

*RQ2: What is the effectiveness of configurations with top-rated analytical tools in achieving short-term business goals?*

*RQ3: How effective are behavioral analytics tools in solving emerging user experience problems?*

*RQ4: How does solving UX and optimization problems affect customer satisfaction and loyalty?*

Prior research has rarely assessed the short-term effectiveness of specific tools and their synergies, therefore, this study fills that gap by providing focused evidence.

### **1 Theoretical background – The essence of behavioral analysis in digital marketing**

Behavioral analytics in digital marketing provides deep insight into user behaviors and preferences, which is crucial for optimizing strategies and improving online performance (Beri & Singh, 2013; Bronnikova et al., 2020). Combined with machine learning, it helps detect cross-platform patterns and forecast consumer actions, enabling personalized, targeted campaigns and strengthening competitive advantage through more relevant content (Aiolfi et al., 2021; Güngör & Çadırcı, 2022; Masrianto et al., 2022). Tools such as Google Analytics and Adobe Analytics allow firms to monitor web and social activity, measure campaign effectiveness, and identify areas for improvement (Beri & Singh, 2013; Hassan & Galal-Edeen, 2017).

Embedding behavioral analytics within a user-centered approach raises satisfaction and engagement; adapting interfaces and content based on empirical evidence increases conversions and builds long-term relationships (Bronnikova et al., 2020; Yasmine & Atmojo, 2022). In a fast-changing environment, where UX competition intensifies and behaviors

evolve, maintaining relevance and personalization is challenging (Güngör & Çadırcı, 2022; Novák et al., 2023).

In e-commerce, UX quality, clear information, easy navigation, and transaction security, drives satisfaction and, in turn, loyalty and recommendation (Wijaya et al., 2021). Evidence links perceived service quality to loyalty via satisfaction (Hansopaheluwakan, 2021) and shows that superior online experiences deepen emotional engagement and reduce sensitivity to rivals (Garcia-Madariaga et al., 2018).

Concrete instruments such as click analysis, heatmaps, and session recordings reveal intuitive versus frustrating elements. Advanced interaction tracking uncovers accessibility and usability obstacles, informing UX optimization and, consequently, loyalty (Buschek et al., 2015). Used continuously, these insights raise conversion, lower churn, and stimulate positive word-of-mouth (Garcia-Madariaga et al., 2018; Hansopaheluwakan, 2021; Wijaya et al., 2021). Because different tools capture different facets of behavior, organizations typically combine complementary instruments to support effective targeting and personalization.

Given functional differences across tools, we group them into six categories to systematize data collection and analysis. This classification clarifies each tool's contribution to marketing processes and improves research clarity and efficiency.

#### **First category – Tools for data analysis**

In e-commerce, social media, and related contexts, behavioral analysis extracts decision-useful insight by collecting, analyzing, and visualizing hard data to understand and segment behaviors, optimize experiences, and support business outcomes (Buschek et al., 2015; Hanamanthrao & Thejaswini, 2017; Menges et al., 2020). Representative systems enable automation, data-driven decision making, and advanced analytics in digital marketing (Alghamdi & Al-Baity, 2022; Baardman et al., 2022; Kacprzak & Hensel, 2023; Ohme et al., 2023) (see Tab. A1 in appendix).

#### **Second category – Tools for testing and optimization**

Testing and optimization tools improve the performance of websites, business profiles, and mobile apps (see Tab. A1 in appendix). A/B testing remains a cornerstone of data-driven

decisions, and reinforcement-learning approaches extend immediate and long-term insight (Haizler & Steinberg, 2021; Shi et al., 2022; Siroker & Koomen, 2013). Optimization is tracked with indicators such as conversion rate, while conversion funnels locate drop-offs and help predict purchase probability (Goldstein et al., 2022; Zimmermann & Auinger, 2022). Personalization platforms support multivariate tests and dynamic offer delivery, and form or visit analytics help identify friction and refine session engagement (Jansen et al., 2022; Sa-deghi et al., 2020).

### Third category – Tools for monitoring user activity

Monitoring tools collect, analyze, and interpret data from multiple digital touchpoints to reveal behaviors, preferences, and needs that inform tailored marketing and product decisions (Anshari et al., 2019) (see Tab. A1 in appendix). Session recordings and replay scripts surface usability patterns, although they raise ethical concerns about unintended personal-data capture (Grodzinsky et al., 2022). Such data often feed CRM strategy and qualify as big data because of scope and processing complexity (Verhoef et al., 2016; Zerbino et al., 2018). Tag management and tracking codes enable agile experimentation, and event or click tracking supports predictive models of engagement and content effectiveness (Al-Qrize, 2023; Wang et al., 2022). Real-time live-stream formats enhance dynamic engagement and purchase intention, while audience networks and pixels sharpen targeting and reach (Addo et al., 2021; Al-Qrize, 2023; Orenaga-Roglá & Chalmeta, 2016; Xu et al., 2023).

### Fourth category – Tools for visual interaction analysis

Visual interaction tools represent user behavior across social media, websites, mobile apps, and e-commerce, supporting interactive analysis and multidimensional visualizations that clarify complex relationships between users and digital properties (Artemenko & Gavrilova, 2023; Drusch et al., 2020; Lipizzi et al., 2016) (see Tab. A1 in appendix). Heatmaps, including zone-based variants, capture clicks, mouse movement, and scroll depth to guide layout and user-flow optimization, while scroll-depth analytics supports scrollytelling approaches and mouse-path analytics adds spatial detail and

satisfaction indicators (Chen et al., 2020; Mörth et al., 2022).

### Fifth category – Tools for collecting feedback and segmentation

Feedback and segmentation tools gather customer opinions, preferences, and shopping behaviors that underpin need identification and strategy design (see Tab. A1 in appendix). Online surveys remain widely used in academic and business settings, although challenges around data integrity and respondent authenticity are growing (Murray et al., 2022; Nur et al., 2023; Tomlin, 2018). Contemporary practice increasingly relies on clustering algorithms, such as *K*-means, and RFMT models to identify high-value segments and target them with personalized content and offers, often within integrated analytics and customer-selection platforms (Salminen et al., 2023; Tomlin, 2018; Ullah et al., 2023).

### Sixth category – Tools for advanced data analysis

Advanced tools and methods filter unwanted traffic and transform data so that reports align with business needs (see Tab. A1 in appendix). Combined session replay, heatmaps, and funnel views uncover friction points and improve customer experience (Gahler et al., 2022; Palazón et al., 2022). Cross-channel content management with real-time journey mapping supports dynamic optimization, and filters can permanently exclude internal traffic using ISP domains, IP addresses, subdirectories, or hostnames, alongside search-and-replace and inclusion or exclusion operations (Ha et al., 2022; Koch et al., 2023; Lundin & Kindström, 2023). As dependence on behavioral and transactional data grows, transparent and privacy-conscious analytics are essential to sustain trust (Plangger, 2023).

## 2 Research methodology

We adopt an information-management approach that systematizes the acquisition, storage, processing, and analysis of multi-source digital data to support marketing decisions (Figueiredo et al., 2021; Piñeiro-Otero & Martínez-Rolán, 2016; Post & Anderson, 2003). The study assesses the effectiveness of behavioral-analytics tools in achieving short-term organizational goals on websites and business profiles in a dynamic consumer environment.

Guided by the systems paradigm, we evaluate both individual effects and interactions, focusing on goal attainment, problem solving, and impacts on loyalty and satisfaction, which reflects a holistic, integrated perspective on decision making.

All analyses were run in Python within Jupyter Notebook using standard libraries for descriptive statistics, Pearson correlations, and OLS/multiple regressions.

**2.1 Hypothesis development**

Behavioral-analytics tools provide deeper analytical capabilities than traditional marketing methods, enabling detailed tracking of online activity and a better understanding of consumer behavior and reactions to campaign changes (Tomlin, 2018). Prior research often emphasized broad strategies rather than tool-level effects and synergies (Yasmin et al., 2015), while tools are frequently used in complementary ways due to their limiting properties (Chen et al., 2012). This motivates testing whether configurations that include top-rated instruments yield more short-term results.

*H1: Synergies with top-rated tools have a strong impact on achieving short-term business goals.*

The effectiveness of tools in solving specific marketing problems remains underexplored (Chaffey & Smith, 2022; Charlesworth, 2020). Firms face issues such as content creation bottlenecks, limited analytics, and low conversion, which require advanced analytics to diagnose and address (Chaffey & Patron, 2012; Leeflang et al., 2014). Measuring effectiveness by the number of problems solved is therefore appropriate for short-term assessment (Yasmine & Atmojo, 2022).

*H2: There is a strong positive correlation between the rating of tools and the number of problems solved.*

Improving UX and interface clarity increases task efficiency, perceived ease, and trust (Babatunde et al., 2024). Reducing friction in navigation and feedback loops raises satisfaction, especially when visual layout and microinteractions match user expectations (Gao & Liu, 2023; Jongmans et al., 2022). Satisfaction

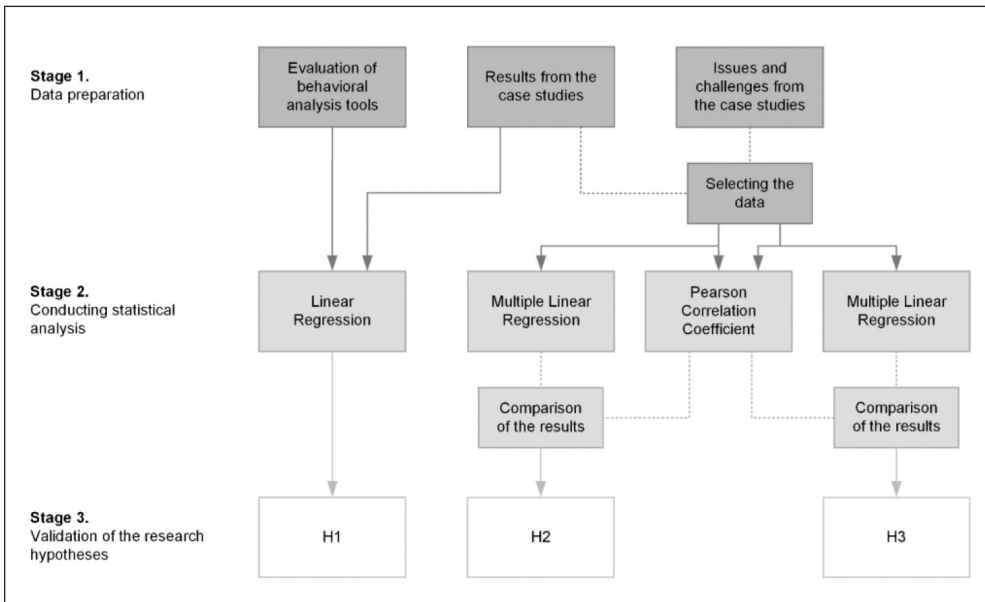


Fig. 1: The process of validating research hypotheses

Source: own

is a proximal driver of loyalty in online services, reflected in repeat use, positive word of mouth, and lower switching intentions (Goutam et al., 2021; Wijaya et al., 2021). When behavioral segmentation and personalization heighten perceived relevance and value, UX gains translate into both attitudinal and behavioral loyalty, which justifies testing whether tools that resolve UX and optimization issues also raise satisfaction and loyalty (Alwan & Alshurideh, 2022; Mohammad, 2022).

*H3: The effectiveness of tools in solving UX and optimization problems is highly positively correlated with their effectiveness in increasing customer satisfaction and loyalty.*

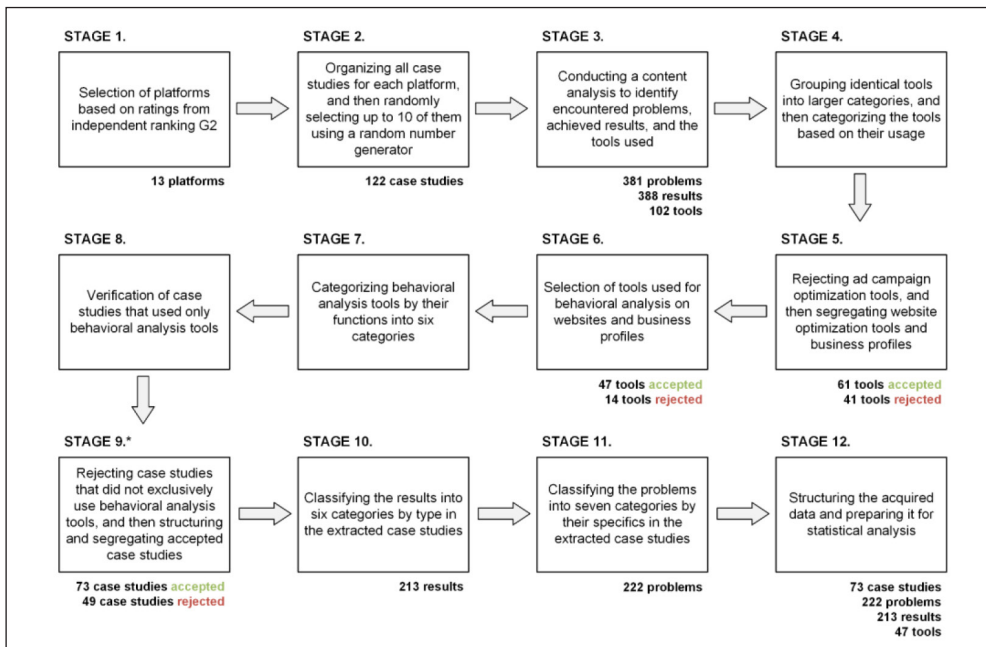
A hypothesis validation process was developed to systematize the stages of the calculations and conclusions, as shown in Fig. 1.

Hypothesis validation proceeded in three stages (Fig. 2). Stage 1 covered data preparation by compiling the evaluation of behavioral analysis tools, results from the case studies,

and issues and challenges, then selecting the data for each hypothesis. Stage 2 applied linear regression, a tool co-occurrence matrix, multiple linear regression, and Pearson correlation in line with the framework: co-occurrence plus linear regression for *H1*, Pearson and multiple linear regression for *H2*, and Pearson and multiple linear regression for *H3*. After each model we compared the results. Stage 3 synthesized the evidence to validate *H1–H3*.

## 2.2 Data collection

We compiled a research base of case studies and analyzed their content to identify tools, uses, outcomes, and problems (all cases collected on October 3, 2023). From the official websites of 12 recognized brands in behavioral analytics, we randomly selected up to 10 texts per site, or included all available descriptions when fewer than 10 were present. Selection followed criteria designed to capture how behavioral tools support UX-oriented optimization, with the screening stages shown in Fig. 2.



**Fig. 2: Stages of case study selection using content analysis**

Note: The selection process excluded all case studies from the Pinterest Business platform.

Source: own

Content analysis, understood as a systematic procedure for describing linguistic features of texts, enabled consistent extraction of variables relevant to digital UX optimization and performance evaluation (Mavi & Uzunboyu, 2014). On this basis, we coded the tools employed, the results obtained, and the problems addressed across organizations.

We treat the identified results as short-term business goals because they reflect rapid responses to current issues, can be measured over

short cycles, and are intended to support quick adaptation to changing digital conditions. Behavioral analytics facilitates fast detection and resolution of user problems, which affects engagement, conversion, and near-term performance.

In total, 73 case studies met the criteria and were subjected to statistical analysis. The selection emphasized analyses of user behavior on websites and business profiles, and Tab. 1 lists the platforms and number of case studies included in the sample.

**Tab. 1: List of platforms included in the study**

No.	Platform	Number of case studies
1	Hotjar	10
2	Google Marketing Platform	6
3	Adobe Experience Platform	5
4	X Business	2
5	Crazy Egg	7
6	Meta Business	1
7	Smartlook	10
8	Fullstory	8
9	Contentsquare	5
10	Mouseflow	5
11	VWO	4
12	Microsoft Clarity	10

Source: own

On platforms such as Hotjar, Crazy Egg, Smartlook, Mouseflow, and Microsoft Clarity, all case studies were positively evaluated during the selection process. The justification for this evaluation directly results from the functionality of the tools offered by these platforms, which are tailored for comprehensive behavioral analysis, from session recordings and heatmaps to business funnels (Langer et al., 2022; Stoiber et al., 2022; Wang et al., 2024).

### 2.3 Data analysis

Based on the research of Hopkins (2001) and Lee (2009), to validate the study results, consultations were conducted with experts who were asked to subjectively assign weights to different categories of results. This allowed

the identification of result groups that experts consider key to the development of organizations in the digital environment.

To select experts, the Scopus bibliographic database was used to verify authors who conducted the most popular studies in the field of digital marketing within management (the author search engine was not used due to its limited ability to specify specialists' areas of interest). To obtain opinions from scientists focused on digital marketing, several restrictions were applied in the search protocol. The selection restrictions were as follows:

**Article title, abstract, keywords:** *“digital marketing”* OR *“online marketing”* OR *“internet marketing”* OR *“e-marketing”*;  
**Year:** *since 2018 to 2024*;

**Subject area:** limited to: business, management and accounting; social sciences; economics, econometrics and finance; decision sciences;

**Document type:** limited to article;

**Source type:** limited to journal;

**Sort by:** cited by (highest).

Five highly cited researchers were contacted via email and three agreed to participate. They are internationally recognized scholars with H-index values of 62, 33, and 12 verified in Scopus on 22/08/2025. Each expert independently assigned weights on a 0–1 scale to six marketing performance categories, and final weights were computed as arithmetic means, which is appropriate in exploratory designs with small panels.

Agreement among experts, assessed with Kendall's  $W$  on rank-transformed weights, was  $W = 0.47$  ( $df = 5$ ,  $p > 0.05$ ), indicating moderate but not statistically significant concordance and constituting a study limitation. Formal consensus methods such as Delphi or the analytic hierarchy process were not implemented because they require larger panels, iterative rounds, and consistency and sensitivity checks that were impractical with asynchronous consultations (Buingo et al., 2024; Lipovetsky, 2009). Averaged weights were then applied

to the structured results extracted from the case studies, and Tab. 2 reports the category weights and the resulting weighted evaluations.

The obtained opinions show a varied approach by experts to the significance of different result categories. Based on the number of results in each category, the type of obtained effects, and the averaged weight of expert assessments, a weighted average was calculated, which was then used to evaluate behavioral analysis tools. As can be seen from the data in Tab. 2, the most valuable results are those from the second category. This implies that each subsequent result from this category achieved by a given tool will increase its rating by 6.29.

The foundation of research on the importance of analyzed tools in digital marketing is their evaluation, which consists of several elements. Primarily, the key determinant is the number of occurrences of tools in the context of achieving individual results. These results, divided into specific result categories for each tool, are then evaluated using the average weight values provided by the experts. The process of synthetic evaluation of tools is presented in Equation (1).

$$E_{BAT} = \sum_{k=1}^K \left( R_k \times \left( \frac{1}{N} \sum_{i=1}^N W_{ik} \right) \times T_{mk} \right) \quad (1)$$

**Tab. 2:** Valuation of individual categories of results

No.	Result categories	Structure of results (%)	Expert 1	Expert 2	Expert 3	Averaged weighting	Weighted evaluation
		[1]	[2]	[3]	[4]	[5]	[6]
1	Increase efficiency and streamline processes	18.78	0.05	0.10	0.15	0.10	1.88
2	Increase conversion rates and improve site optimization	31.46	0.35	0.10	0.15	0.20	6.29
3	Increase in interaction and user engagement	8.92	0.25	0.20	0.20	0.22	1.93
4	Increase in satisfaction and customer loyalty	15.49	0.05	0.40	0.20	0.22	3.36
5	Improved content and design management	9.86	0.25	0.10	0.20	0.18	1.81
6	Reduced costs and increased savings	15.49	0.05	0.10	0.10	0.08	1.29

Note: The average was calculated using the following formula:  $([2] + [3] + [4])/3$ ; the weighted average was calculated using the following formula:  $[1] \times [5]$ .

Source: own

where:  $E_{BAT}$  – evaluation of behavioral analysis tool;  $K$  – number of result categories;  $R_k$  – the tool's contribution to the outcome structure in category  $k$ ;  $N$  – number of experts;  $W_{ik}$  – weight of the result category assigned by expert  $i$  for category  $k$ ;  $T_{mk}$  – number of occurrences of tool  $m$  in result category  $k$ .

The methodological foundations of tool evaluation enable a deeper understanding

of the conducted research and allow for a broader spectrum of conclusions, which can then influence the acceptance or rejection of the research hypotheses. Aggregating tool evaluations across different categories allows for comparison between various classifications, ultimately facilitating the identification of the most effective tools in achieving specific business goals.

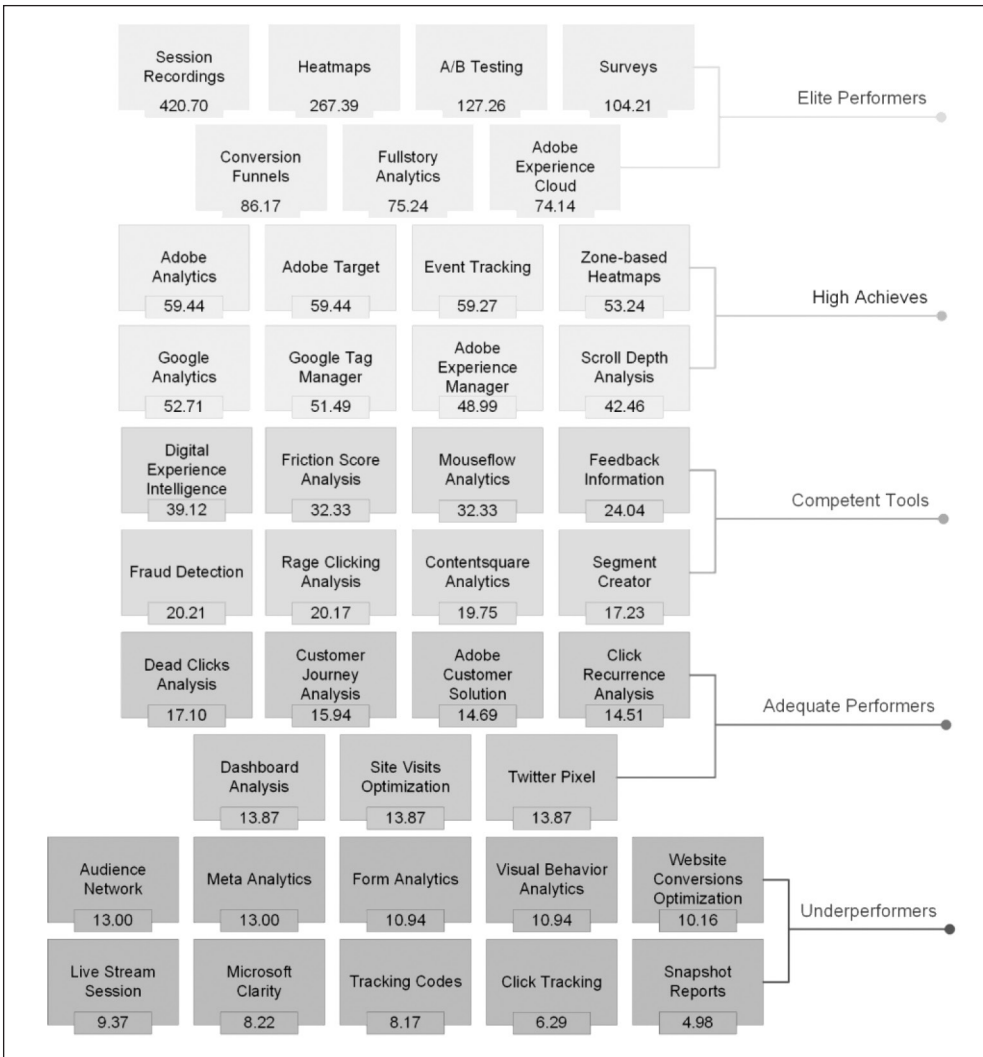


Fig. 3: Aggregate evaluation of analytical tools for behavioral analysis

Source: own

### 3 Results

#### 3.1 Evaluation of analytical tools for behavioral analysis

Tools for data analysis and visualization totaled 183.13, mean 30.52 per tool, with Adobe Analytics 59.44 and Google Analytics 52.71 leading, and Facebook Insights 13.00 and Snapshot Reports 4.98 lowest. Testing and optimization tools reached 392.93, mean 49.12, led by A/B Testing 127.26 and Conversion Funnels 86.17, while Site Visits Optimization 13.87 and Website Conversions Optimization 10.16 ranked lowest. In monitoring user activity, Session Recordings dominated with 420.70, ahead of Event Tracking 59.27, whereas Tracking Codes 8.17, Click Tracking 6.29, and Twitter Pixel 13.87 scored low, consistent with limited

contributions to heavily weighted outcome categories (see Tab. 2A–4A, appendix). Fig. 3 presents a hierarchical summary of tools based on the obtained results.

Fig. 3 summarizes aggregate scores in quintiles. Top performers include Session Recordings (420.70), Heatmaps (267.39), and A/B Testing (127.26).

#### 3.2 Co-occurrence of tools in achieving short-term business goals

To examine synergies among top-rated tools, we built a co-occurrence matrix from case-level pairings and compared counts with outcomes by category and in total (Tab. 3). We then estimated linear regressions for each category and for the total results.

**Tab. 3: Matrix of most frequent co-occurrences with top-rated tools**

Tools		Sum of co-occurrences	Results categories						Total
			1	2	3	4	5	6	
Session Recordings	Heatmaps	21	9	23	7	15	5	3	62
Session Recordings	Fullstory Analytics	7	4	3	4	4	2	3	20
Conversion Funnels	Session Recordings	6	7	4	2	5	6	3	27
Surveys	Session Recordings	5	2	7	1	4	1	0	15
Adobe Experience Cloud	Adobe Analytics	5	4	7	1	3	3	4	22
Heatmaps	Conversion Funnels	4	4	3	2	5	3	2	19
A/B Testing	Zone-based Heatmaps	4	2	5	2	1	0	2	12
Surveys	Heatmaps	4	0	7	1	3	1	0	12
Fullstory Analytics	Digital Experience Intelligence	4	3	2	2	3	1	4	15
Adobe Experience Cloud	Adobe Target	4	2	6	1	2	3	3	17
A/B Testing	Segment Creator	2	0	2	0	1	0	1	4

Note: The result category numbers are the same as in Tab. A2 (appendix).

Source: own

The pairing of Session Recordings with Heatmaps dominates with 21 co-occurrences. A/B Testing shows limited synergy in this sample, with 4 co-occurrences with Zone-based Heatmaps and 2 with Segment Creator. Synergies between two top-rated tools are common, with six such pairings, four of which involve Session Recordings.

We regressed the sum of results on the number of co-occurrences to quantify the association for each category and in total (Tab. 4).

Each additional co-occurrence is associated with a 2.8295 increase in the total results. The largest category effect is for category 2 (coef = 1.0606), and the smallest for category 6

**Tab. 4: Linear regression analysis for tool co-occurrence and results**

Specification	Results categories						Sum of results
	1	2	3	4	5	6	
Coefficient (coef)	0.4205	1.0606	0.3447	0.7197	0.2159	0.0682	2.8295
p-value	0.0040	0.0000	0.0000	0.0000	0.0680	0.4650	0.0000
R <sup>2</sup> value							0.9360

Note: The result category numbers are the same as in Tab. A2 (appendix).

Source: own

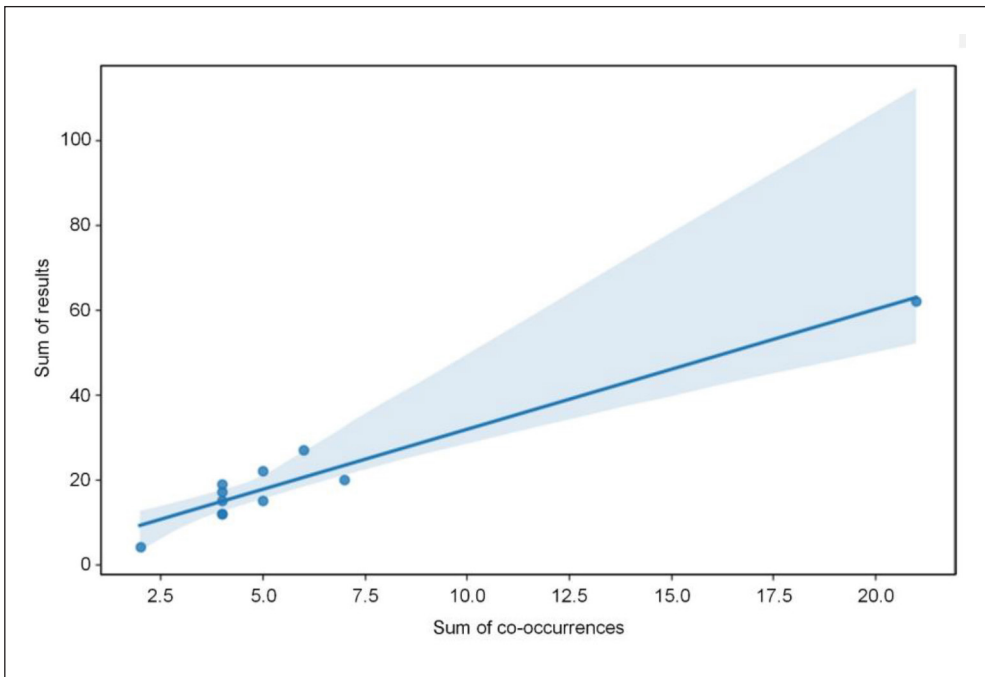
(coef = 0.0682). Results for categories 5 and 6 are not statistically significant ( $p = 0.068$  and  $p = 0.465$ , respectively).

Fig. 4 visualizes the relationship between tool co-occurrences and results.

The total-results model is statistically significant ( $p < 0.001$ ), indicating a strong link between the frequency of co-occurrences and outcomes.

### 3.3 Ability of analytical tools to solve problems

We confirmed homoscedasticity with the Breusch-Pagan test ( $p = 0.547 > 0.05$ ), so we used Pearson correlations and complemented them with multiple regression. For Pearson, we compiled per-tool sums of ratings and sums of problems across categories.



**Fig. 4: Linear regression graph for tool co-occurrence and result**

Source: own

**Tab. 5: Pearson correlation coefficient for tool ratings and problems**

Specification	Correlation coefficient	p-value	
Problem categories	1	0.9378	4.717e-19
	2	0.9726	1.1045e-25
	3	0.8503	3.8385e-12
	4	0.8770	1.1584e-13
	5	0.9224	2.7444e-17
	6	0.9176	8.2278e-17
	7	0.8980	4.0292e-15
<b>Sum of problems</b>	<b>0.9888</b>	<b>5.3214e-33</b>	

Note: Problem categories in the table have been numbered to better show the correlation coefficients. The list is as follows: 1 – problems and challenges related to data acquisition and analysis, 2 – problems and challenges related to user experience and optimization, 3 – problems and challenges related to user segmentation and personalization, 4 – problems and challenges related to information management and internal processes, 5 – problems and challenges related to conversion and efficiency, 6 – problems and challenges related to the use of technology and tools, 7 – problems and challenges related to communication and flow of information from users and customers.

Source: own

**Tab. 6: Multiple linear regression analysis results for tool ratings and individual problem categories**

Specification	Regression coefficient (coef)	p-value	R <sup>2</sup> value	
Problem categories	1	0.9378	4.7170e-19	0.991
	2	0.9726	1.1045e-25	
	3	0.8503	3.8385e-12	
	4	0.8770	1.1584e-13	
	5	0.9224	2.7444e-17	
	6	0.9176	8.2278e-17	
	7	0.8980	4.0292e-15	

Note: The problem category numbers are the same as in Tab. A2 (appendix).

Source: own

Tool ratings show strong positive associations with problems solved, with the highest correlation for UX and optimization (category 2) and still high values for the remaining categories. We next estimated a multiple regression to profile category contributions.

We regressed tool ratings on counts of solved problems by category to quantify their relative effects (Tab. 6).

Model fit is high ( $R^2 = 0.991$ ). Category 2 exhibits the largest effect on ratings, while

the detailed coefficients and p-values for all categories are reported in Tab. 6.

### 3.4 Impact of tool effectiveness in solving UX and optimization problems on increasing customer satisfaction and loyalty

Homoscedasticity was satisfied (Breusch-Pagan  $p = 0.424 > 0.05$ ), so we applied Pearson and multiple regression. We prepared two datasets: per-tool sums of solved UX and

Tab. 7:

**Multiple linear regression analysis for results related to increased customer loyalty and satisfaction and individual problem categories**

Specification		Regression coefficient (coef)	p-value	R <sup>2</sup> value
Problem categories	1	0.1209	0.140	0.976
	2	0.4285	0.000	
	3	-0.1169	0.200	
	4	0.2096	0.070	
	5	0.3972	0.004	
	6	-0.0132	0.863	
	7	0.3213	0.005	

Note: The problem category numbers are the same as in Tab. A2 (appendix).

Source: own

optimization problems, and per-tool sums of satisfaction and loyalty outcomes. The correlation is very high ( $r = 0.9646$ ,  $p < 0.001$ ), and the regression model shows strong fit ( $R^2 = 0.976$ ).

Effects are strongest for category 2, with additional significant contributions from categories 5 and 7; other categories are not statistically significant. These results indicate that solving UX and optimization issues is most closely linked to gains in satisfaction and loyalty.

## 4 Discussion

### 4.1 Evaluation of analytical tools for behavioral analysis

The results show that tools enabling real-time, in-depth tracking of user interactions are rated highest, especially those for monitoring user activity and visual interaction analysis, because they reveal usability issues, guide interface improvements, and optimize engagement paths (Filip & Čegan, 2019). This pattern reflects a shift from static measurement to dynamic, user-centered insight, where session recordings and heatmaps support rapid problem detection and sustained gains in UX, conversion, and retention (Saeidi & Baradari, 2023). Their value also stems from broad applicability and integration with other instruments across the customer journey.

By comparison, feedback and segmentation tools remain important for personalization and profiling yet play a more complementary role in short-term optimization, which underscores the need to align tool choice with specific goals and process stages (Khomenko et al., 2021;

Wang, 2022). Overall, the evidence supports frameworks such as AARRR and the growing use of AI-powered analytics, highlighting multi-channel visibility, predictive modeling, and immediate behavioral insight as capabilities that help firms adapt to changing expectations and maintain advantage (Theodorakopoulos & Theodoropoulou, 2024).

### 4.2 Co-occurrence of tools in achieving short-term business goals

Effective digital marketing depends on combining complementary tools into cohesive systems that support tactical and strategic goals (Järvinen & Karjaluoto, 2015). Our co-occurrence analysis shows that high-performing tools operate synergistically, especially Elite Performers (see Fig. 3), with Session Recordings and Heatmaps the dominant pairing in user journeys. This synergy aligns with evidence that granular behavioral data, visualized and interpreted dynamically, improves customer insight and enables timely design changes (Čegan & Filip, 2017; Ziemba et al., 2018), and with the logic of online behavioral advertising, where real-time signals drive more personalized and persuasive experiences (Aiolfi et al., 2021; Varnali, 2019).

We also observe brand-exclusive synergies in the Adobe ecosystem, where internal compatibility is high and external integration more limited, yet the suite still performs well in UX optimization. This mirrors broader trends in AI-driven marketing, in which proprietary stacks maximize automation, personalization, and campaign efficiency within defined

environments (Han et al., 2021; Van Esch & Black, 2021). Statistically, each additional tool co-occurrence increases total results by 2.8295, with the strongest gains in conversion and site optimization and weaker effects for content governance or cost reduction, and model fit is high,  $R^2 = 0.936$ . Given the strength and consistency of these results, we accept *H1* that synergies with top-rated tools have a strong impact on achieving short-term business goals (Giakomidou et al., 2022; Masrianto et al., 2022).

### 4.3 Ability of analytical tools to solve problems

Our evaluation shows a strong link between tool effectiveness and problem solving, with user experience and optimization issues exerting the greatest influence on expert ratings. This aligns with evidence that interface friction, poor navigation, and slow interactions drive dissatisfaction and abandonment, so tools that expose and resolve these issues are rated higher. We also find significant contributions from tools that address information management and internal processes, as well as communication and information flow from users, which reflects the value of integrated feedback loops, real-time content delivery, and streamlined workflows supported by AI and machine learning, including causal and reinforcement approaches (Gubela et al., 2022; Koch et al., 2023; Ngai & Wu, 2022).

By contrast, segmentation and personalization, conversion and efficiency, and technology or tool implementation show non-significant relationships with scores in our model, suggesting a lower direct contribution to the short-term tactical outcomes prioritized in this evaluation. These patterns are consistent with research on visual analytics and content modeling, which emphasizes understanding sequences, motivations, and pain points through direct interaction data rather than audience identity alone (Kietzmann & Pitt, 2020; Wu & Yu, 2020). Given these results, *H2* is accepted.

### 4.4 Impact of tool effectiveness in solving UX and optimization problems on increasing customer satisfaction and loyalty

Addressing UX and optimization issues shows a very strong association with satisfaction and loyalty outcomes,  $r = 0.9646$ , and the regression model indicates that each additional UX or optimization problem solved increases

these outcomes by about 0.43, the largest effect among all categories. This pattern is consistent with evidence that website quality and usability mechanisms drive satisfaction and loyalty, and that predictive UX analytics and behavioral visualizations help detect friction and enable timely interface improvements (Chen et al., 2023; Ferreira et al., 2022; Garcia-Madariaga et al., 2018; Nan et al., 2022). Taken together, the statistical results and prior research indicate that solving UX and optimization problems is the most direct pathway to short-term gains in satisfaction and loyalty, therefore, *H3* is accepted.

### 4.5 Practical implications of behavioral analytics tool evaluation

Select tools based on demonstrated ability to deliver priority outcomes. Highest-scoring instruments, particularly session tracking, A/B testing, heatmap visualization, and conversion funnels, are consistently associated with higher conversion, better UX, greater satisfaction, and process efficiency. A/B testing enables data-driven, cost-effective optimization (Guha et al., 2021; Mandić et al., 2023; Siroker & Koomen, 2013), while session recordings and deep-learning behavior models support highly personalized, adaptive strategies (Batool, 2023; Li, 2022).

The most effective stacks combine diagnostic insight with predictive personalization. Heatmaps reveal engagement and friction and guide content and interface redesign (Koehn et al., 2020), session recordings provide granular behavioral evidence (Nesterenko et al., 2023), and conversion funnels locate drop-offs and improve flow (Proença & Moraes, 2023). Used together these tools generate measurable synergies, reflected in the significant link between co-occurrence and outcomes ( $R^2 = 0.936$ ). By contrast, Snapshot Reports and basic Click Tracking show limited strategic value, indicating surface-level metrics. In practice, deploy complementary, goal-oriented stacks, apply A/B testing iteratively to validate UX or content decisions (Guha et al., 2021; Mandić et al., 2023; Siroker & Koomen, 2013), let session- and funnel-based evidence inform personalization, segmentation, and conversion strategies, and integrate behavioral data with CRM and performance analytics for a holistic view of user behavior.

## Conclusions

This study shows that the strategic value of behavioral analytics tools depends on alignment

with clearly defined business objectives, not only on technical capabilities. Session recordings and heatmaps are particularly effective for diagnosing UX issues and achieving short-term goals such as higher satisfaction and conversion, and their combined use provides a comprehensive view of behavior that enables targeted improvements to experience and engagement. The findings also highlight the importance of integration and synergy, especially among top-rated solutions, while stressing that impact depends on coherent implementation and continuous evaluation against business-specific metrics as user behavior evolves.

Practically, organizations should adopt an iterative, data-driven workflow that incorporates user feedback, behavioral segmentation, and real-time analytics, and invest in solutions that support seamless integration, predictive insight, and adaptive UX. Future research should validate expert-based assessments with larger empirical datasets linking tools to user performance indicators and campaign outcomes. Overall, behavioral analytics is foundational to modern digital marketing and supports the achievement of key business objectives in a complex and fast-changing environment.

**Limitations and future recommendations.** The study relies on selected case studies, which limits generalizability, and the tool set does not cover the full market. Expert weighting is another constraint: three experts with H-index values of 62, 33, and 12 produced Kendall's  $W = 0.47$ , a moderate but non-significant agreement likely due to the small panel. Averaging weights is a defensible choice in exploratory work given the experts' standing, but results should be interpreted with caution. Future research should expand the expert pool, apply formal consensus methods with consistency checks and sensitivity analyses within integrated decision frameworks, and triangulate expert judgments with empirical evidence from campaigns, including conversion metrics, A/B test outcomes, and engagement statistics.

## References

- Addo, C. P., Fang, J., Asare, A. O., & Kulbo, N. B. (2021). Customer engagement and purchase intention in live-streaming digital marketing platforms. *The Service Industries Journal*, 41(11–12), 767–786. <https://doi.org/10.1080/02642069.2021.1905798>
- Aiolfi, S., Bellini, S., & Pellegrini, D. (2021). Data-driven digital advertising: Benefits and risks of online behavioral advertising. *International Journal of Retail & Distribution Management*, 49(7), 1089–1110. <https://doi.org/10.1108/IJRDM-10-2020-0410>
- Alfian, G., Ijaz, M. F., Syafrudin, M., Syaek-honi, M. A., Fitriyani, N. L., & Rhee, J. (2019). Customer behavior analysis using real-time data processing: A case study of digital signage-based online stores. *Asia Pacific Journal of Marketing and Logistics*, 31(1), 265–290. <https://doi.org/10.1108/APJML-03-2018-0088>
- Alghamdi, N. A., & Al-Baity, H. H. (2022). Augmented analytics driven by AI: A digital transformation beyond business intelligence. *Sensors*, 22(20), 8071. <https://doi.org/10.3390/s22208071>
- Al-Qrize, F. (2023). Popularity-driven metrics: Audience analytics and shifting opinion power to digital platforms. *Journalism Studies*, 24(3), 403–421. <https://doi.org/10.1080/1461670x.2023.2167104>
- Alwan, M., & Alshurideh, M. (2022). The effect of digital marketing on value creation and customer satisfaction. *International Journal of Data and Network Science*, 6(4), 1557–1566. <https://doi.org/10.5267/j.ijdns.2022.4.021>
- Anshari, M., Almunawar, M. N., Lim, S. A., & Al-Mudimigh, A. (2019). Customer relationship management and big data enabled: Personalization & customization of services. *Applied Computing and Informatics*, 15(2), 94–101. <https://doi.org/10.1016/j.aci.2018.05.004>
- Artemenko, E. A., & Gavrilova, T. V. (2023). Heatmaps as optimization of marketing solutions to increase the informative content of the website. *CRJ*, 1(2), 60–63. <https://doi.org/10.59380/crj.v1i2.2740>
- Baardman, L., Cristian, R., Perakis, G., Singhvi, D., Skali Lami, O., & Thayaparan, L. (2022). The role of optimization in some recent advances in data-driven decision-making. *Mathematical Programming*, 200(1), 1–35. <https://doi.org/10.1007/s10107-022-01874-9>
- Babatunde, S. O., Odejide, O. A., Edunjobi, T. E., & Ogundipe, D. O. (2024). The role of AI in marketing personalization: A theoretical exploration of consumer engagement strategies. *International Journal of Management & Entrepreneurship Research*, 6(3), 936–949. <https://doi.org/10.51594/ijmer.v6i3.964>
- Batool, I. (2023). *A deep learning approach for the online user behaviour prediction using*

*clickstream data* [Preprint]. SSRN. <https://doi.org/10.2139/ssrn.4662627>

Beri, B., & Singh, P. (2013). Web analytics: Increasing website's usability and conversion rate. *International Journal of Computer Applications*, 72(6), 35–38. <https://doi.org/10.5120/12501-8420>

Bronnikova, E., Kuljamina, O., & Vinogradova, M. (2020). Application of modern models of behavioral economics in internet branding. *GIS Business*, 15(1), 81–94.

Bugingo, E., Leone Ndimubenshi, E., Tshimanga Kamanga, C., Xavier Rugema, F., Habimana, O., & Batumuliza, J. (2024). Application of AHP in Decision-Making: Case Studies and Practical Implementation. In F. De Felice & A. Petrillo (Ed.), *Business, Management and Economics* (Vol. 29). IntechOpen. <https://doi.org/10.5772/intechopen.1006966>

Buschek, D., Auch, A., & Alt, F. (2015). A toolkit for analysis and prediction of touch targeting behaviour on mobile websites. In *Proceedings of the 7th ACM SIGCHI Symposium on Engineering Interactive Computing Systems*, (Vol. 15, pp. 54–63). EICS. <https://doi.org/10.1145/2774225.2774851>

Čegan, L., & Filip, P. (2017). Detection of errors in the layout design of websites for mobile devices based on capturing user behaviour. *Journal of Communications*, 12(8), 457–463. <https://doi.org/10.12720/jcm.12.8.457-463>

Chaffey, D., & Patron, M. (2012). From web analytics to digital marketing optimization: Increasing the commercial value of digital analytics. *Journal of Direct, Data and Digital Marketing Practice*, 14(1), 30–45. <https://doi.org/10.1057/dddmp.2012.20>

Chaffey, D., & Smith, P. (2022). *Digital marketing excellence: Planning, optimizing and integrating online marketing*. Routledge. <https://doi.org/10.4324/9781003009498>

Charlesworth, A. (2020). *Absolute essentials of digital marketing*. Routledge. <https://doi.org/10.4324/9781003015789>

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly*, 36(4), 1165–1188. <https://doi.org/10.2307/41703503>

Chen, L., Fan, A., Shi, H., & Chen, G. (2020). Region-action LSTM for mouse interaction sequence based search satisfaction evaluation. *Information Processing and Management*, 57(6), 102349. <https://doi.org/10.1016/J.IPM.2020.102349>

Chen, Q., Lu, Y., Gong, Y., & Xiong, J. (2023). Can AI chatbots help retain customers? Impact of AI service quality on customer loyalty. *Internet Research*, 33(6), 2205–2243. <https://doi.org/10.1108/intr-09-2021-0686>

Davidavičienė, V., Sabaitytė, J., Davidavičius, S., & Potapov, M. (2014). Interaction with customers using website tools: Analysis of Lithuanian manufacturing sector. *Procedia – Social and Behavioral Sciences*, 110, 1262–1270. <https://doi.org/10.1016/j.sbspro.2013.12.973>

Drusch, G., Bastien, C. J. M., & Paris, S. (2020). Analysing eye-tracking data: From scanpaths and heatmaps to the dynamic visualisation of areas of interest. In T. Marek (Ed.), *Proceedings of AHFE (2020) International Conference. Advances in Science, Technology, Higher Education and Society in the Conceptual Age: STHESCA. AHFE Open Access* (Vol. 10). AHFE International. <https://doi.org/10.54941/ahfe100394>

Ferreira, J. M., Rodríguez, F. D., Santos, A., Dieste, O., Acuña, S. T., & Juristo, N. (2022). Impact of usability mechanisms: A family of experiments on efficiency, effectiveness and user satisfaction. *IEEE Transactions on Software Engineering*, 49(1), 251–267. <https://doi.org/10.1109/tse.2022.3149586>

Figueiredo, F., Gonçalves, M. J. A., & Teixeira, S. (2021). Information technology adoption on digital marketing: A literature review. *Informatics*, 8(4), 74. <https://doi.org/10.3390/informatics8040074>

Filip, P., & Čegan, L. (2019). Comparing tools for web-session recording and replaying. In *Proceedings of 2019 International Conference on Sustainable Information Engineering and Technology (SIET)* (Vol. 257–260). IEEE. <https://doi.org/10.1109/siet48054.2019.8986134>

Gahler, M., Klein, J. F., & Paul, M. (2022). Customer experience: Conceptualization, measurement, and application in omnichannel environments. *Journal of Service Research*, 26(2), 191–211. <https://doi.org/10.1177/10946705221126590>

Gao, Y., & Liu, H. (2023). Artificial intelligence-enabled personalization in interactive marketing: A customer journey perspective. *Journal of Research in Interactive Marketing*, 17(5), 663–680. <https://doi.org/10.1108/JRIM-01-2022-0023>

García-Madariaga, J., Recuero Virto, N., Blasco López, M. F., & Aldas Manzano, J.

(2018). Optimizing website quality: The case of two superstar museum websites. *International Journal of Culture, Tourism and Hospitality Research*, 13(1), 16–36. <https://doi.org/10.1108/IJCTHR-06-2018-0074>

Giakomidou, D. S., Kriemadis, A., Nasiopoulos, D. K., & Mastrakoulis, D. (2022). Re-engineering of marketing for SMEs in energy market through modeling customers. *Energies*, 15(21), 8179. <https://doi.org/10.3390/en15218179>

Goldstein, A., Oestreicher-Singer, G., Barzilay, O., & Yahav, I. (2022). Are we there yet? Analyzing progress in the conversion funnel using the diversity of searched products. *MIS Quarterly*, 46(4), 2015–2054. <https://doi.org/10.25300/misq/2022/15524>

Goutam, D., Gopalakrishna, B. V., & Ganguli, S. (2021). Determinants of customer satisfaction and loyalty in e-commerce settings: An emerging economy perspective. *International Journal of Internet Marketing and Advertising*, 15(3), 327–348. <https://doi.org/10.1504/IJIMA.2021.115437>

Grodzinsky, F. S., Miller, K. W., & Wolf, M. J. (2022). Session replay scripts: A privacy analysis. *The Information Society*, 38(4), 257–268. <https://doi.org/10.1080/01972243.2022.2078916>

Gubela, R. M., Lessmann, S., & Stöcker, B. (2022). Multiple treatment modeling for target marketing campaigns: A large-scale benchmark study. *Information Systems Frontiers*, 26(3), 875–898. <https://doi.org/10.1007/s10796-022-10283-4>

Guha, P., Echagarruga, C., & Tian, E. Q. (2021). Optimising marketing strategies by customer segments and lifetime values, with A/B testing. *Applied Marketing Analytics*, 7(2), 144. <https://doi.org/10.69554/jzjw5041>

Güngör, A. S., & Çadırcı, T. O. (2022). Understanding digital consumer: A review, synthesis, and future research agenda. *International Journal of Consumer Studies*, 46(5), 1829–1858. <https://doi.org/10.1111/ijcs.12809>

Ha, S., Monadjemi, S., Garnett, R., & Otley, A. (2022). A unified comparison of user modeling techniques for predicting data interaction and detecting exploration bias. *IEEE Transactions on Visualization and Computer Graphics*, 29(1), 483–492. <https://doi.org/10.1109/tvcg.2022.3209476>

Haizler, T., & Steinberg, D. M. (2021). Factorial designs for online experiments. *Techno-*

*metrics*, 63(1), 1–12. <https://doi.org/10.1080/00401706.2019.1701556>

Han, R., Lam, H. K. S., Zhan, Y., Wang, Y., Dwivedi, Y. K., & Tan, K. H. (2021). Artificial intelligence in business-to-business marketing: A bibliometric analysis of current research status, development and future directions. *Industrial Management & Data Systems*, 121(12), 2467–2497. <https://doi.org/10.1108/imds-05-2021-0300>

Hanamanthrao, R., & Thejaswini, S. (2017). Real-time clickstream data analytics and visualization. In *Proceedings of 2017 2<sup>nd</sup> IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)* (pp. 2139–2144). IEEE. <https://doi.org/10.1109/RTEICT.2017.8256978>

Hansopaheluwakan, S. (2021). Analysis of e-service quality and website quality effect on e-customer loyalty through e-customer satisfaction (case study: Tokopedia). *IOP Conference Series: Earth and Environmental Science*, 794(1), 012086. <https://doi.org/10.1088/1755-1315/794/1/012086>

Hassan, H. M., & Galal-Edeen, G. H. (2017). From usability to user experience. In *Proceedings of 2017 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS)* (pp. 216–222). IEEE. <https://doi.org/10.1109/ICIIBMS.2017.8279761>

Hopkins, L. D. (2001). Multi-attribute decision making in urban studies. In N. J. Smelser & P. B. Baltes (Eds), *International encyclopedia of the social & behavioral sciences* (pp. 10157–10160). Elsevier. <https://doi.org/10.1016/B0-08-043076-7/04437-5>

Huang, S.-L., & Lin, Y.-H. (2022). Exploring consumer online purchase and search behavior: An FCB grid perspective. *Asia Pacific Management Review*, 27(4), 245–256. <https://doi.org/10.1016/j.apmr.2021.10.003>

Jansen, B. J., Jung, S., & Salminen, J. (2022). Measuring user interactions with websites: A comparison of two industry standard analytics approaches using data of 86 websites. *PLOS ONE*, 17(5), e0268212. <https://doi.org/10.1371/journal.pone.0268212>

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>

Jongmans, E., Jeannot, F., Liang, L., & Dampérat, M. (2022). Impact of website

- visual design on user experience and website evaluation: The sequential mediating roles of usability and pleasure. *Journal of Marketing Management*, 38(17–18), 2078–2113. <https://doi.org/10.1080/0267257X.2022.2085315>
- Kacprzak, A., & Hensel, P. (2023). Exploring online customer experience: A systematic literature review and research agenda. *International Journal of Consumer Studies*, 47(6), 2583–2608. <https://doi.org/10.1111/ijcs.12966>
- Khomenko, L., Saher, L., Letunovska, N., & Jasnikowski, A. (2021). Segmentation as a base for digital marketing strategies in blood service: A cluster analysis for classifying healthy regional subjects. *E3S Web of Conferences*, 307, 03001. <https://doi.org/10.1051/e3sconf/202130703001>
- Kietzmann, J., & Pitt, L. F. (2020). Computerized content analysis of online data – Opportunities for marketing scholars and practitioners. *European Journal of Marketing*, 54(3), 473–477. <https://doi.org/10.1108/ejm-01-2020-0007>
- Koch, C., Lindenbeck, B., & Olbrich, R. (2023). Dynamic customer journey analysis and its advertising impact. *Journal of Strategic Marketing*, 1–20. <https://doi.org/10.1080/0965254x.2023.2171475>
- Koehn, D., Lessmann, S., & Schaal, M. (2020). Predicting online shopping behaviour from clickstream data using deep learning. *Expert Systems with Applications*, 150, 113342. <https://doi.org/10.1016/j.eswa.2020.113342>
- Langer, T., Meyes, R., & Meisen, T. (2022). Gideon replay: A library to replay interactions in web-applications. *SoftwareX*, 17, 100964. <https://doi.org/10.1016/j.softx.2021.100964>
- Lee, A. H. I. (2009). A fuzzy supplier selection model with the consideration of benefits, opportunities, costs and risks. *Expert Systems with Applications*, 36(2), 2879–2893. <https://doi.org/10.1016/j.eswa.2008.01.045>
- Leeflang, P. S. H., Verhoef, P. C., Dahlström, P., & Freundt, T. (2014). Challenges and solutions for marketing in a digital era. *European Management Journal*, 32(1), 1–12. <https://doi.org/10.1016/j.emj.2013.12.001>
- Li, Z. (2022). Accurate digital marketing communication based on intelligent data analysis. *Scientific Programming*, 2022, 1–10. <https://doi.org/10.1155/2022/8294891>
- Lipizzi, C., Dessavre, D. G., Iandoli, L., & Marquez, J. E. R. (2016). Social media conversation monitoring: Visualize information contents of twitter messages using conversational metrics. *Procedia Computer Science*, 80, 2216–2220. <https://doi.org/10.1016/j.procs.2016.05.384>
- Lipovetsky, S. (2009). Optimal hierarchy structures for multi-attribute-criteria decisions. *Journal of Systems Science and Complexity*, 22(2), 228–242. <https://doi.org/10.1007/s11424-009-9159-5>
- Lundin, L., & Kindström, D. (2023). Digitalizing customer journeys in B2B markets. *Journal of Business Research*, 157, 113639. <https://doi.org/10.1016/j.jbusres.2022.113639>
- Manchia, M., Gathier, A. W., Yapici-Eser, H., Schmidt, M. V., de Quervain, D., van Amelsvoort, T., Bisson, J. I., Cryan, J. F., Howes, O. D., Pinto, L., van der Wee, N. J., Domschke, K., Branchi, I., & Vinkers, C. H. (2022). The impact of the prolonged COVID-19 pandemic on stress resilience and mental health: A critical review across waves. *European Neuropsychopharmacology*, 55, 22–83. <https://doi.org/10.1016/j.euroneuro.2021.10.864>
- Mandić, M., Gregurec, I., & Vujović, U. (2023). Measuring the effectiveness of online sales by conducting A/B testing. *Market-Tržište*, 35(2), 223–249. <https://doi.org/10.22598/mt/2023.35.2.223>
- Masrianto, A., Hartoyo, H., Hubeis, A. V. S., & Hasanah, N. (2022). Digital marketing utilization index for evaluating and improving company digital marketing capability. *Journal of Open Innovation: Technology, Market, and Complexity*, 8(3), 153. <https://doi.org/10.3390/joitmc8030153>
- Mavi, D., & Uzunboylu, H. (2014). Content analysis of articles about computer teaching methods: A content analysis study. *Procedia – Social and Behavioral Sciences*, 143, 1171–1176. <https://doi.org/10.1016/j.sbspro.2014.07.573>
- Menges, R., Kramer, S., Hill, S., Nisslmueller, M., Kumar, C., & Staab, S. (2020). A visualization tool for eye tracking data analysis in the web [Short paper]. In *Proceedings of ACM Symposium on Eye Tracking Research and Applications. ETRA, 20 Short Papers* (No. 46, pp. 1–5). ETRA. <https://doi.org/10.1145/3379156.3391831>
- Miah, M. R., Hossain, A., Shikder, R., Saha, T., & Neger, M. (2022). Evaluating the impact of social media on online shopping behavior during COVID-19 pandemic: A Bangladeshi consumers' perspectives. *Heliyon*, 8(9), e10600. <https://doi.org/10.1016/j.heliyon.2022.e10600>

- Miklosik, A., Kuchta, M., Evans, N., & Zak, S. (2019). Towards the adoption of machine learning-based analytical tools in digital marketing. *IEEE Access*, 7, 85705–85718. <https://doi.org/10.1109/ACCESS.2019.2924425>
- Mohammad, A. A. S. (2022). The impact of digital marketing success on customer loyalty. *Marketing and Management of Innovations*, 13(3), 103–113. <https://doi.org/10.21272/mmi.2022.3-09>
- Mörth, E., Bruckner, S., & Smit, N. N. (2022). *ScrollyVis: Interactive visual authoring of guided dynamic narratives for scientific scrollytelling* [arXiv:2207.03616]. ArXiv. <https://doi.org/10.48550/arxiv.2207.03616>
- Murray, H., Kerr, A., Warnock-Parkes, E., Wild, J., Grey, N., Clark, D. M., & Ehlers, A. (2022). What do others think? The why, when and how of using surveys in CBT. *The Cognitive Behaviour Therapist*, 15. <https://doi.org/10.1017/s1754470x22000393>
- Nan, D., Shin, E., Barnett, G. A., Cheah, S., & Kim, J. H. (2022). Will coolness factors predict user satisfaction and loyalty? Evidence from an artificial neural network–structural equation model approach. *Information Processing & Management*, 59(6), 103108. <https://doi.org/10.1016/j.ipm.2022.103108>
- Nesterenko, V. G., Miśkiewicz, R., & Abazov, R. (2023). Marketing communications in the era of digital transformation. *Virtual Economics*, 6(1), 57–70. <https://doi.org/10.34021/ve.2023.06.01>
- Ngai, E. W. T., & Wu, Y. (2022). Machine learning in marketing: A literature review, conceptual framework, and research agenda. *Journal of Business Research*, 145, 35–48. <https://doi.org/10.1016/j.jbusres.2022.02.049>
- Novák, J. Š., Masner, J., Benda, P., Šimek, P., & Merunka, V. (2023). Eye tracking, usability, and user experience: A systematic review. *International Journal of Human-Computer Interaction*, 40(17), 4484–4500. <https://doi.org/10.1080/10447318.2023.2221600>
- Nur, A. A., Leibbrand, C., Curran, S. R., Votruba-Drzal, E., & Gibson-Davis, C. (2023). Managing and minimizing online survey questionnaire fraud: Lessons from the Triple C project. *International Journal of Social Research Methodology*, 27(5), 613–619. <https://doi.org/10.1080/13645579.2023.2229651>
- Ohme, J., Araujo, T., Boeschoten, L., Freelon, D., Ram, N., Reeves, B. B., & Robinson, T. N. (2023). Digital trace data collection for social media effects research: APIs, data donation, and (screen) tracking. *Communication Methods and Measures*, 18(2), 124–141. <https://doi.org/10.1080/19312458.2023.2181319>
- Orenga-Roglá, S., & Chalmeta, R. (2016). Social customer relationship management: Taking advantage of Web 2.0 and Big Data technologies. *SpringerPlus*, 5(1), 1462. <https://doi.org/10.1186/s40064-016-3128-y>
- Palazón, M., López, M., Sicilia, M., & López, I. (2022). The customer journey: A proposal of indicators to evaluate integration and customer orientation. *Journal of Marketing Communications*, 28(5), 528–559. <https://doi.org/10.1080/13527266.2022.2051584>
- Piñeiro-Otero, T., & Martínez-Rolán, X. (2016). Understanding digital marketing – Basics and actions. In C. Machado & J. P. Davim (Eds), *MBA: Theory and application of business and management principles* (pp. 37–74). Springer International Publishing. [https://doi.org/10.1007/978-3-319-28281-7\\_2](https://doi.org/10.1007/978-3-319-28281-7_2)
- Plangger, K., Marder, B., Montecchi, M., Watson, R., & Pitt, L. (2023). Does (customer data) size matter? Generating valuable customer insights with less customer relationship risk. *Psychology and Marketing*, 40(10), 2016–2028. <https://doi.org/10.1002/mar.21866>
- Post, G. V., & Anderson, D. L. (2003). *Management information systems*. McGraw-Hill.
- Proença, H. M., & Moraes, F. (2023). *Incremental profit per conversion: A response transformation for uplift modeling in e-commerce promotions* [arXiv:2306.13759]. ArXiv. <https://doi.org/10.48550/arxiv.2306.13759>
- Sadeghi, S., Chien, P., & Arora, N. (2020). Sliced designs for multi-platform online experiments. *Technometrics*, 62(3), 387–402. <https://doi.org/10.1080/00401706.2019.1647288>
- Saeidi, S., & Baradari, Z. (2023). Examining the correlation between metrics in the Instagram social network to identify fake pages and improve marketing. *Computers in Human Behavior Reports*, 12, 100341. <https://doi.org/10.1016/j.chbr.2023.100341>
- Salminen, J., Mustak, M., Sufyan, M., & Jansen, B. J. (2023). How can algorithms help in segmenting users and customers? A systematic review and research agenda for algorithmic customer segmentation. *Journal of Marketing Analytics*, 11(4), 677–692. <https://doi.org/10.1057/s41270-023-00235-5>
- Saura, J. R. (2021). Using data sciences in digital marketing: Framework, methods,

and performance metrics. *Journal of Innovation & Knowledge*, 6(2), 92–102. <https://doi.org/10.1016/j.jik.2020.08.001>

Shi, C., Wang, X., Luo, S., Zhu, H., Ye, J., & Song, R. (2022). Dynamic causal effects evaluation in A/B testing with a reinforcement learning framework. *Journal of the American Statistical Association*, 118(543), 2059–2071. <https://doi.org/10.1080/01621459.2022.2027776>

Siroker, D., & Koomen, P. (2013). *A/B testing: The most powerful way to turn clicks into customers*. Wiley Publishing.

Stoiber, C., Walchshofer, C., Pohl, M., Potzmann, B., Grassinger, F., Stitz, H., Streit, M., & Aigner, W. (2022). Comparative evaluations of visualization onboarding methods. *Visual Informatics*, 6(4), 34–50. <https://doi.org/10.1016/j.visinf.2022.07.001>

Theodorakopoulos, L., & Theodoropoulou, A. (2024). Leveraging big data analytics for understanding consumer behavior in digital marketing: A systematic review. *Human Behavior and Emerging Technologies*, 2024(1). <https://doi.org/10.1155/2024/3641502>

Tomlin, W. C. (2018). *UX optimization: Combining behavioral UX and usability testing data to optimize websites*. Apress. <https://doi.org/10.1007/978-1-4842-3867-7>

Treboux, J., Cretton, F., Evequoz, F., Calve, A. L., & Genoud, D. (2016). Mining and visualizing social data to inform marketing decisions. In *Proceedings of 2016 IEEE 30<sup>th</sup> International Conference on Advanced Information Networking and Applications (AINA)* (pp. 66–73). IEEE. <https://doi.org/10.1109/AINA.2016.130>

Ullah, A., Mohmand, M. I., Hussain, H., Johar, S., Khan, I., Ahmad, S., Mahmoud, H. A., & Huda, S. (2023). Customer analysis using machine learning-based classification algorithms for effective segmentation using recency, frequency, monetary, and time. *Sensors*, 23(6), 3180. <https://doi.org/10.3390/s23063180>

Van Esch, P., & Black, J. S. (2021). Artificial intelligence (AI): Revolutionizing digital marketing. *Australasian Marketing Journal*, 29(3), 199–203. <https://doi.org/10.1177/183933492111037684>

Varnali, K. (2019). Online behavioral advertising: An integrative review. *Journal of Marketing Communications*, 27(1), 93–114. <https://doi.org/10.1080/13527266.2019.1630664>

Verhoef, P. C., Kooge, E., & Walk, N. (2016). *Creating value with big data analytics: Making smarter marketing decisions*. Routledge. <https://doi.org/10.4324/9781315734750>

Wang, C. (2022). Efficient customer segmentation in digital marketing using deep learning with swarm intelligence approach. *Information Processing & Management*, 59(6), 103085. <https://doi.org/10.1016/j.ipm.2022.103085>

Wang, D., Galster, M., & Morales-Trujillo, M. (2024). Application monitoring for bug reproduction in web-based applications. *Journal of Systems and Software*, 207, 111834. <https://doi.org/10.1016/j.jss.2023.111834>

Wang, Q., Liu, F., Zhao, X., & Tan, Q. (2022). A CTR prediction model based on session interest. *PLOS ONE*, 17(8), e0273048. <https://doi.org/10.1371/journal.pone.0273048>

Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing*, 80(6), 97–121. <https://doi.org/10.1509/jm.15.0413>

Wijaya, I. G. N. S., Triandini, E., Kabnani, E. T. G., & Arifin, S. (2021). E-commerce website service quality and customer loyalty using WebQual 4.0 with importance performances analysis, and structural equation model: An empirical study in Shopee. *Register: Jurnal Ilmiah Teknologi Sistem Informatika*, 7(2), 107–124. <https://doi.org/10.26594/register.v7i2.2266>

Wu, I.-C., & Yu, H.-K. (2020). Sequential analysis and clustering to investigate users' online shopping behaviors based on need-states. *Information Processing & Management*, 57(6), 102323. <https://doi.org/10.1016/j.ipm.2020.102323>

Xu, Y., Kapitana, S., & Phillips, M. (2023). The commercial impact of live streaming: A systematic literature review and future research agenda. *International Journal of Consumer Studies*, 47(6), 2495–2527. <https://doi.org/10.1111/ijcs.12960>

Yasmin, A., Tasneem, S., & Fatema, K. (2015). Effectiveness of digital marketing in the challenging age: An empirical study. *The International Journal of Management Science and Business Administration*, 1(5), 69–80. <https://doi.org/10.18775/ijmsba.1849-5664-5419.2014.15.1006>

Yasmine, H. T., & Atmojo, W. T. (2022). UI/UX design for tourism village website using the user centered design method. *TIERS Information Technology Journal*, 3(2), 100–114. <https://doi.org/10.38043/tiers.v3i2.3871>

Zerbino, P., Aloini, D., Dulmin, R., & Mininno, V. (2018). Big data-enabled customer relationship management: A holistic approach.

*Information Processing & Management*, 54(5), 818–846. <https://doi.org/10.1016/j.ipm.2017.10.005>

Ziemba, Y. C., Lomsadze, L., Jacobs, Y., Chang, T. Y., & Haghi, N. (2018). Using heatmaps to identify opportunities for optimization of test utilization and care delivery. *Journal of*

*Pathology Informatics*, 9(1), 31. [https://doi.org/10.4103/jpi.jpi\\_7\\_18](https://doi.org/10.4103/jpi.jpi_7_18)

Zimmermann, R., & Auinger, A. (2022). Developing a conversion rate optimization framework for digital retailers – Case study. *Journal of Marketing Analytics*, 11(2), 233–243. <https://doi.org/10.1057/s41270-022-00161-y>

## Appendix

Tab. A1: Detailed classification of tools

Classification	Tool
Tools for data analysis	Adobe Analytics
	Facebook Insights
	Google Analytics
	Digital Experience Intelligence
	Dashboard Analysis
	Snapshot Reports
Tools for testing and optimization	A/B Testing
	Adobe Experience Cloud
	Adobe Target
	Conversions Funnels
	Website Conversions Optimization
	Site Visits Optimization
	Form Analytics
Visual Behavior Analytics	
Tools for monitoring user activity	Session Recordings
	Google Tag Manager
	Event Tracking
	Live Stream Session
	Audience Network
	Tracking Codes
	Twitter Pixel
	Click Tracking
Click Recurrence Analysis	
Tools for visual interaction analysis	Heatmaps
	Zone-based Heatmaps
	Scroll Depth Analysis
	Mouseflow Analytics
Tools for collecting feedback and segmentation	Surveys
	Feedback Information
	Segment Creator
	Adobe Customer Selection
Tools for advanced data analysis	Fullstory Analytics
	Contentsquare Analytics
	Adobe Experience Manager
	Customer Journey Analytics
	Dead Clicks Analysis
	Friction Score Analysis
	Rage Clicking Analysis
	Fraud Detection
Clarity	

Source: own

**Tab. A2: Evaluation of data analysis tools**

Specification		Result categories						Total
		1	2	3	4	5	6	
<b>Data analysis tools</b>		<b>16.90</b>	<b>100.66</b>	<b>7.73</b>	<b>30.21</b>	<b>10.85</b>	<b>16.78</b>	<b>183.13</b>
1	<b>Adobe Analytics</b>	3.76	37.75	1.93	6.71	5.42	3.87	59.44
2	<b>Google Analytics</b>	5.63	31.46	1.93	6.71	1.81	5.16	52.71
3	<b>Digital Experience Intelligence</b>	5.63	12.58	3.87	10.07	1.81	5.16	39.12
4	<b>Dashboard Analysis</b>	–	12.58	–	–	–	1.29	13.87
5	<b>Facebook Insights</b>	–	6.29	–	6.71	–	–	13.00

Note: Result categories in the table were numbered to better present the results of the evaluation of individual tools. The list is as follows: 1 – increase in efficiency and process improvement, 2 – increase in conversion rates and improvement in site optimization, 3 – increase in user interaction and engagement, 4 – increase in customer satisfaction and loyalty, 5 – better content and design management, 6 – reduction of costs and increase in savings; inconsistency in the result with ratings from individual table cells may result from rounding the sum to two decimal places.

Source: own

**Tab. A3: Evaluation of testing and optimization tools**

Specification		Result categories						Total
		1	2	3	4	5	6	
<b>Testing and optimization tools</b>		<b>30.05</b>	<b>232.77</b>	<b>15.46</b>	<b>60.42</b>	<b>27.11</b>	<b>27.11</b>	<b>392.93</b>
1	<b>A/B Testing</b>	5.63	88.08	7.73	20.14	1.81	3.87	127.26
2	<b>Conversion Funnels</b>	13.15	31.46	3.87	16.78	14.46	6.46	86.17
3	<b>Adobe Experience Cloud</b>	7.51	44.04	1.93	10.07	5.42	5.16	74.14
4	<b>Adobe Target</b>	3.76	37.75	1.93	6.71	5.42	3.87	59.44
5	<b>Site Visits Optimization</b>	–	12.58	–	–	–	1.29	13.87
6	<b>Form Analytics</b>	–	6.29	–	3.36	–	1.29	10.94
7	<b>Visual Behavior Analytics</b>	–	6.29	–	3.36	–	1.29	10.94
8	<b>Website Conversions Optimization</b>	–	6.29	–	–	–	3.87	10.16

Note: The result category numbers are the same as in Tab. A2 (appendix); inconsistency in the result with ratings from individual table cells may result from rounding the sum to two decimal places.

Source: own

**Tab. A4: Evaluation of user activity monitoring tools**

Specification		Result categories						Total
		1	2	3	4	5	6	
<b>User activity monitoring tools</b>		<b>73.24</b>	<b>327.14</b>	<b>32.86</b>	<b>97.35</b>	<b>32.54</b>	<b>33.57</b>	<b>596.68</b>
1	Session Recordings	41.31	232.77	27.06	77.21	21.69	20.66	420.70
2	Event Tracking	16.90	18.87	–	6.71	9.04	7.75	59.27
3	Google Tag Manager	7.51	31.46	1.93	6.71	–	3.87	51.49
4	Click Recurrence Analysis	–	12.58	1.93	–	–	–	14.51
5	Twitter Pixel	–	12.58	–	–	–	1.29	13.87
6	Audience Network	–	6.29	–	6.71	–	–	13.00
7	Live Stream Session	5.63	–	1.93	–	1.81	–	9.37
8	Tracking Codes	1.88	6.29	–	–	–	–	8.17
9	Click Tracking	–	6.29	–	–	–	–	6.29

Note: The result category numbers are the same as in Tab. A2 (appendix); inconsistency in the result with ratings from individual table cells may result from rounding the sum to two decimal places.

Source: own

**Tab. A5: Evaluation of visual interaction analysis tools**

Specification		Result categories						Total
		1	2	3	4	5	6	
<b>Visual interaction analysis tools</b>		<b>39.44</b>	<b>239.06</b>	<b>27.06</b>	<b>67.14</b>	<b>16.27</b>	<b>6.46</b>	<b>395.41</b>
1	Heatmaps	24.41	157.28	15.46	53.71	12.65	3.87	267.39
2	Zone-based Heatmaps	3.76	37.75	5.80	3.36	–	2.58	53.24
3	Scroll Depth Analysis	9.39	18.87	3.87	6.71	3.62	–	42.46
4	Mouseflow Analytics	1.88	25.16	1.93	3.36	–	–	32.33

Note: The result category numbers are the same as in Tab. A2 (appendix); inconsistency in the result with ratings from individual table cells may result from rounding the sum to two decimal places.

Source: own

**Tab. A6: Evaluation of feedback collection and segmentation tools**

Specification		Result categories						Total
		1	2	3	4	5	6	
<b>Tools for feedback collection and segmentation</b>		<b>11.27</b>	<b>106.95</b>	<b>1.93</b>	<b>30.21</b>	<b>7.23</b>	<b>2.58</b>	<b>160.17</b>
1	Surveys	7.51	69.20	1.93	20.14	5.42	–	104.21
2	Feedback Information	–	18.87	–	3.36	1.81	–	24.04
3	Segment Creator	–	12.58	–	3.36	–	1.29	17.23
4	Adobe Customer Solution	3.76	6.29	–	3.36	–	1.29	14.69

Note: The result category numbers are the same as in Tab. A2 (appendix); inconsistency in the result with ratings from individual table cells may result from rounding the sum to two decimal places.

Source: own

**Tab. A7: Evaluation of advanced analysis tools**

Specification		Result categories						Total
		1	2	3	4	5	6	
<b>Advanced analysis tools</b>		<b>24.41</b>	<b>157.28</b>	<b>17.39</b>	<b>33.57</b>	<b>7.23</b>	<b>18.08</b>	<b>257.96</b>
1	Fullstory Analytics	11.27	31.46	7.73	13.43	3.62	7.75	75.24
2	Adobe Experience Manager	3.76	37.75	–	–	3.62	3.87	48.99
3	Friction Score Analysis	1.88	25.16	1.93	3.36	–	–	32.33
4	Fraud Detection	3.76	12.58	–	–	–	3.87	20.21
5	Rage Clicking Analysis	1.88	6.29	1.93	10.07	–	–	20.17
6	Contentsquare Analytics	1.88	12.58	1.93	3.36	–	–	19.75
7	Dead Clicks Analysis	–	12.58	1.93	–	–	2.58	17.10
8	Customer Journey Analysis	–	12.58	–	3.36	–	–	15.94
9	Clarity	–	6.29	1.93	–	–	–	8.22

Note: The result category numbers are the same as in Tab. A2 (appendix); inconsistency in the result with ratings from individual table cells may result from rounding the sum to two decimal places.

Source: own