УДК 65.011.56:004.8 https://doi.org/10.31520/ei.2026.28.1(98).108-120
JEL: C52; C89; D83; D91; L15, L86; M31

received date: 2026-01-06, revised date: 2026-02-04, accepted date: 2026-03-02, published date: 2026-03-20

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ПРОАКТИВНИЙ МЕНЕДЖМЕНТ ЯКОСТІ В ЕПОХУ ШТУЧНОГО ІНТЕЛЕКТУ: ВІД ДЕТЕКЦІЇ «СИГНАЛІВ ФРУСТРАЦІЇ» ДО ГІПЕР-ПЕРСОНАЛІЗАЦІЇ

Актуальність. *В умовах глобальної конкуренції, підвищення вимог до якості цифрових продуктів відбувається цифрова трансформація менеджменту якості в умовах активного впровадження технологій штучного інтелекту. Традиційні підходи до забезпечення якості виявляються недостатніми для вирішення сучасних викликів, пов'язаних зі змінами навколишнього середовища та необхідністю обробки великих обсягів даних. Такі обставини обумовлюють фундаментальну трансформацію підходів до забезпечення якості (QA) цифрових продуктів із застосуванням технологій штучного інтелекту. Вплив цифрової економіки на процес забезпечення якості цифрових продуктів обумовлює необхідність переходу від моделі реактивної корекції помилок до проактивного управління клієнтським досвідом (CX). Досвід провідних технологічних компаній (Uber, Airbnb, Duolingo) демонструє приклади застосування алгоритмів машинного навчання для автоматичного виявлення «сигналів фрустрації», моніторингу бізнес-аномалій та створення гіпер-персоналізованих інтерфейсів. Для створення цифрових продуктів, які точно відповідають потребам споживачів, необхідною умовою є конвергенція маркетингових технологій та управління якістю. Такий підхід перетворює якість на інструмент маркетингу, орієнтуючись на задоволення вимог клієнта та сталий розвиток.*

Мета та завдання. *Метою є обґрунтування необхідності переходу від реактивної моделі забезпечення якості цифрового продукту до проактивної системи управління досвідом користувача, що базується на технологіях штучного інтелекту. Мета дослідження обумовила необхідність вирішення наступних завдань: обґрунтувати наявну кризу реактивного QA та довести економічну необхідність проактивності; аргументувати необхідність використання предиктивної аналітики для прогнозування майбутніх подій та вузьких місць у клієнтському досвіді; розглянути можливості застосування штучного інтелекту в якості діагностичного інструменту для покращення якості цифрового продукту; здійснити порівняльний огляд інструментів для поведінкової аналітики, класифікованих за моделлю доступності та специфікою застосування, обґрунтувати гіпер-персоналізацію у забезпеченні якості цифрового продукту.*

Матеріали та методи. *Теоретичну основу дослідження становить аналіз наукових публікацій, аналітичних звітів та тематичних досліджень провідних технологічних компаній у сфері цифрового маркетингу, управління якістю та застосування штучного інтелекту. Для досягнення поставленої мети було використано методи порівняльного аналізу, узагальнення та систематизації наукових підходів до управління якістю цифрових продуктів, а також елементи контент-аналізу публікацій, присвячених впровадженню рішень штучного інтелекту в QA та UX. У статті систематизовано методи автоматизованої детекції «сигналів фрустрації», інструменти гіпер-персоналізації, які дозволяють виявляти та усувати проблеми взаємодії до усвідомлення їх клієнтом.*

Результати дослідження. *У статті розглянуто концептуальні засади трансформації менеджменту якості у сфері цифрових продуктів. Обґрунтовано трансформацію підходів до забезпечення якості (QA) цифрових продуктів під впливом технологій штучного інтелекту. Авторами запропоновано перехід від моделі реактивної корекції помилок до проактивного управління клієнтським досвідом (CX). Здійснено аналіз тематичних досліджень провідних технологічних компаній з практичного використання алгоритмів машинного навчання у процесі забезпечення якості продуктів та гіпер-персоналізації. Запропоновано цикл персоналізації, який передбачає активне використання штучного інтелекту у процесі аналізу даних про поведінку користувача. Доведено доцільність синергетичного поєднання ШІ з алгоритмами машинного навчання, які дозволять* *забезпечити персоналізацію в необхідному масштабі. За результатами аналізу практичних кейсів визначено, що використання алгоритмів машинного навчання для детекції «сигналів фрустрації» дозволяє оцифрувати емоційний стан користувачів та перетворити суб'єктивні відчуття на точні інженерні дані. Обґрунтовано необхідність конвергенції маркетингових технологій та інженерних практик QA у процесі забезпечення якості продукту.*

Висновки. *Здійснене дослідження дозволило дійти висновку, що в умовах цифрових трансформацій традиційна модель забезпечення якості цифрового продукту, яка базується на реактивних принципах, є неефективною. Підхід до задоволення потреб споживачів на основі персоналізації вимагає від розробників цифрового продукту забезпечення якості на етапі його розробки. Використання штучного інтелекту для переходу до проактивної моделі управління якістю дозволить діагностувати і передбачати можливі майбутні проблем, пов'язані з якістю продукту. Такий підхід робить акцент на попередженні проблем, а не їх виявленні після застосування продукту. Однією з важливих особливостей застосування штучного інтелекту у забезпеченні якості цифрового продукту є його здатність автоматично виявляти та класифікувати «сигнали фрустрації. Доведено ефективність застосування систем машинного навчання у розпізнаванні патернів поведінки користувачів. В результаті компанії отримують можливість діагностування та вирішення проблем у користувацькому досвіді, а також збереження існуючих клієнтів і залучення нових.*

Ключові слова: *менеджмент якості, штучний інтелект (AI), управління якістю (QA), досвід користувача (UX), клієнтський досвід (CX), проактивний менеджмент, детекція аномалій, сигнали фрустрації, гіпер-персоналізація, генеративний інтерфейс користувача, поведінкова аналітика.*

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PROACTIVE QUALITY MANAGEMENT IN THE ERA OF ARTIFICIAL INTELLIGENCE: FROM DETECTION OF "FRUSTRATION SIGNALS" TO HYPER-PERSONALIZATION

Topicality. *In the context of global competition, increasing requirements for the quality of digital products, a digital transformation of quality management is undergoing a digital transformation driven by the active introduction of artificial intelligence technologies. Traditional approaches to quality assurance are insufficient to address modern challenges associated with environmental changes and the need to process large amounts of data. Such circumstances necessitate a fundamental transformation of approaches to quality assurance (QA) of digital products under the influence of artificial intelligence technologies. The impact of the digital economy on the process of ensuring the quality of digital products necessitates a transition from a reactive error correction model to proactive customer experience management (CX). The experience of leading technology companies (Uber, Airbnb, Duolingo) demonstrates examples of the use of machine learning algorithms to automatically detect "frustration signals", monitor business anomalies and create hyper-personalized interfaces. To create digital products that precisely meet consumer needs, the convergence of marketing technologies and quality management is a necessary condition. This approach turns quality into a marketing tool, focusing on meeting customer requirements and sustainable development.*

Aim and tasks. *The aim is to justify the need to transition from a reactive model of digital product quality assurance to a proactive user experience management system based on artificial intelligence technologies. The aim of the study necessitated the following tasks: to justify the existing crisis of reactive QA and prove the economic necessity of proactivity; to argue for the need to use predictive analytics to predict future events and bottlenecks in the customer experience; to consider the possibilities of using artificial intelligence as a diagnostic tool to improve the quality of a digital product; to carry out a comparative review of behavioral analytics tools classified by availability model and application specificity, to justify hyper-personalization in ensuring the quality of a digital product.*

Materials and Methods. *The theoretical basis of the study is the analysis of scientific publications, analytical reports and case studies of leading technology companies in the field of digital marketing, quality management and the use of artificial intelligence. To achieve the goal, methods of comparative analysis, generalization and systematization of* *scientific approaches to quality management of digital products were used, as well as elements of content analysis of publications dedicated to the implementation of artificial intelligence solutions in QA and UX. The article systematizes methods of automated detection of "frustration signals", hyper-personalization tools that allow you to identify and eliminate interaction problems before the client realizes them.*

Research results. *The article examines the conceptual principles of the transformation of quality management in the field of digital products. The transformation of approaches to quality assurance (QA) of digital products under the influence of artificial intelligence technologies is substantiated. The authors propose a transition from the reactive error correction model to proactive customer experience management (CX). The analysis of case studies of leading technology companies on the practical use of machine learning algorithms in the process of ensuring product quality and hyper-personalization is carried out. A personalization cycle is proposed, which involves the active use of artificial intelligence in the process of analyzing data on user behavior. The feasibility of a synergistic combination of AI with machine learning algorithms, which will allow personalization on the required scale, is proven. Based on the results of the analysis of practical cases, it is determined that the use of machine learning algorithms to detect "frustration signals" allows digitizing the emotional state of users and transforming subjective feelings into accurate engineering data. The need for convergence of marketing technologies and QA engineering practices in the process of ensuring product quality is substantiated.*

Conclusion. *The conducted research led to the conclusion that in the conditions of digital transformations, the traditional model of ensuring the quality of a digital product, which is based on reactive principles, is ineffective. The approach to meeting the needs of consumers based on personalization requires digital product developers to ensure quality at the stage of its development. Using artificial intelligence to transition to a proactive quality management model will allow diagnosing and predicting possible future problems related to product quality. This approach emphasizes preventing problems, rather than identifying them after the product is used. One of the important features of the use of artificial intelligence in ensuring the quality of a digital product is its ability to automatically detect and classify "frustration signals". The effectiveness of using machine learning systems in recognizing user behavior patterns has been proven. As a result, companies gain the opportunity to diagnose and solve problems in the user experience, as well as retain existing customers and attract new ones.*

Keywords: *quality management, artificial intelligence (AI), quality management (QA), user experience (UX), customer experience (CX), proactive management, anomaly detection, frustration signals, hyper-personalization, Generative UI, behavioral analytics.*

Problem statement and its connection with important scientific and practical tasks. The modern digital economy is showing a trend of transition from consumption of goods to consumption of experiences. In this new approach, information services such as interactive software as a service (SaaS), media platforms, e-books, online learning and many others become not just a product with a fixed value, but a dynamic environment of continuous interaction with the user. This causes a change in the understanding of the concept of "product quality", transforming it from static compliance with specifications to an indicator measured in real time at every stage of the customer journey.

Traditional approaches to quality management (QA), which historically focused on identifying technical errors and compliance with formal standards, are becoming insufficient to ensure competitiveness in the new environment. In the creative economy, quality is increasingly determined not by technical perfection, but by the subjective perception of the user, his customer experience (CX) and user experience (UX). Studies confirm that up to 70% of failures of new digital products are associated with imperfect UX design and failure to satisfy the hidden needs of the audience, rather than with technical errors (Tamara, Matyagina, 2025).

Such trends are bringing to the fore the challenges of digital product quality management, which lie at the intersection of engineering and marketing. Marketing technologies are rapidly evolving through the integration of artificial intelligence (AI) and machine learning algorithms, transforming from a lead generation and promotion tool into a key mechanism for proactive quality management.

Analysis of recent publications on the problem. Issues related to behavioral analytics and user frustration signals are addressed in publications by researchers and practitioners such as Adam Bunker (Adam, Bunker, 2024), Sophie Grigoryan (Sophie, Grigoryan, 2025), Dylan Ander (Dylan, Ander, 2025), who analyze in detail the nature, causes, and methods for detecting rage clicks, dead clicks, error clicks, and mouse thrashing. The patterns and laws of the psychology of user frustration are discussed in the scientific paper (Morten, Hertzum, Kasper, Hornbæk, 2023).

Research in the field of personalization and real-time optimization of experience is devoted to the works of Jackie Ziznewski (Jackie, Ziznewski, 2024) and Kailey Boucher (Kailey, Boucher, 2025). Issues of quality management transformation in the era of artificial intelligence are considered in the work of Brian Martin (Brian, Martin, 2024).

The use of hyper-personalization and adaptive interfaces based on AI in the context of improving the user experience is described in the works of Sahla Feroc (Sahla, Feroc, 2024) and Lukas Kincel (Lukas, Kincel, 2025). Thus, (Sahla, Feroc, 2024) offers prospects for the future of UX design, justifies the directions of personalization based on artificial intelligence, explains the technology of neo-interactional design. (Lukas, Kincel, 2025), the head of the innovation department argues for hyper-personalization in mobile interfaces: how personalization using artificial intelligence improves UX. Hyper-personalization, as a fundamental concept, is considered in detail in the publication of Matthew Finio and Amanda Downie (Matthew, Finio, Amanda, Downie, 2024), who define it as a deep adaptation of experience based on micro-segmentation and real-time analysis.

The economic aspect of the speed of value delivery and its impact on user retention is analyzed in a study (Michele, Morales, 2025), which covers more than 2600 companies. Fundamental and applied aspects of using machine learning for anomaly detection, content personalization and automated service recovery are described in detail in technical publications of engineering teams of global technology leaders, such as Uber (uVitals system), Airbnb (machine learning algorithms for object ranking and search query distribution) and Duolingo (gamification and adaptive learning trajectories) (Uber, 2023; Revolut, 2024, Sakshi, Jonwal, 2025).

The article (Telnov, A., Reshmidilova, S., Kulatskyi, V., 2025) argues for the need to improve the quality of digital products in the field of information services to ensure their competitiveness in the market in the context of the development of Industry 5.0. The authors describe the path of creating a digital product, determine indicators and methods for assessing its quality, analyzed the applied marketing tools in quality management.

Allocation of previously unsolved parts of the general problem. Despite significant scientific achievements in the field of quality management and the development of the concept of hyper-personalization, the issues of further substantiation of the conceptual and methodological foundations of proactive customer experience management and practical aspects of the application of artificial intelligence and machine learning as tools for proactive quality management remain an extremely relevant topic of scientific and applied research.

Formulation of research objectives (problem statement). The purpose of the article is a comprehensive analysis of the use of AI within marketing technologies to ensure a strategic transition from a reactive model of post-facto error correction to predictive formation of a seamless customer experience.

The aim of the study necessitated the following tasks: to justify the existing crisis of reactive QA and prove the economic necessity of proactivity; to argue for the need to use predictive analytics to predict future events and bottlenecks in the customer experience; to consider the possibilities of using artificial intelligence as a diagnostic tool to improve the quality of a digital product; to carry out a comparative review of behavioral analytics tools classified by availability model and application specificity, to justify hyper-personalization in ensuring the quality of a digital product.

Materials and Methods. The methodological basis of the study was formed using a set of general scientific and special research methods. Content analysis was used to analyze scientific publications, analytical reports and practical examples of leading technology companies (Uber, Airbnb, Duolingo, Revolut, Endeavor Group, Amazon) in order to identify current trends in understanding the quality of digital products and the role of artificial intelligence in quality management. This method allowed us to identify key concepts such as user frustration signals, hyper-personalization and proactive diagnostics. The system analysis method was used to understand the relationships between user behavior signals, technical quality metrics, marketing indicators and business results of companies. This method allowed us to build a picture of the transition from a reactive to a proactive quality management model.

The comparative analysis method was used to compare traditional approaches to quality assurance with the latest AI methods, which allowed us to identify changes in the understanding of quality and the role of AI as an active participant in the quality management process. Synthesis methods were used to develop a conceptual scheme of the “personalization feedback loop”, which visualizes the process of transforming behavioral data into improved user experience and growth in business metrics. The information base for the study was the technical documentation of software developers, analytical reports of international consulting companies (Contentsquare Benchmark Reports, Amplitude Product Report) and materials from engineering blogs of the studied companies.

An outline of the main results and their justification. The traditional quality assurance model has historically been based on reactive principles that have been established over decades and have become the industry standard. In this paradigm, the quality process is linear and sequential: first, functionality is developed, then testing in an isolated, controlled environment, then the product is released to production, and after operation, the company begins to respond to bug reports or user complaints that come to support services. In such a model, quality is ensured at the development stage, and users act as a kind of “testers” in reality.

With high competition, low switching costs, and a wide choice of digital alternatives, this approach is becoming ineffective. Users are no longer bound to companies emotionally or contractually – they can switch to a competitor, and often they do so instantly, without warning.

Research shows that 88% of consumers are less likely to return to a website or app after a negative experience (0222 Digital Agency, 2025). This metric should be understood as an economic signal: each negative experience means the loss of not only one transaction, but also future repeat purchases, referrals, and potential long-term customer value. According to industry data, acquiring a new customer costs 5-25 times more than retaining an existing one. Therefore, losing even one satisfied customer due to a reactive approach to quality is not just a UX problem, but an economic problem for the company.

A particularly critical phenomenon for business, which has long been ignored by companies, is the so-called “silent churn” crisis. This phenomenon reveals a fundamental gap between what companies describe as the quality of their product and the real situation. Thus, studies show that only 1 in 26 dissatisfied customers finds the time, energy and motivation to write a complaint or report a quality problem to the company. This means that the other 25 customers switch to competitors without any formal signal from the company that they are dissatisfied. They close the browser, delete the application or simply stop using the service (Adam, Bunker, 2024).

A 2025 Amplitude study, which analyzed over 2,600 companies, found that 91% of new users are likely to abandon a product within the first week if they don’t get value quickly (Michele, Morales, 2025). This creates a misleading impression for companies that rely solely on the number of support tickets as a metric of quality and customer satisfaction. If a company sees that the number of support tickets is low, it may assume that all users are happy. In reality, this means that most dissatisfied users simply don’t report a complaint.

The reactive QA model causes hidden economic costs that are often underestimated, namely:

– complaint handling costs (each complaint that reaches the support service requires personnel costs, investigation time, documentation and customer compensation or retention benefits);

– bug detection and correction costs (when a bug is already detected in production for millions of users, the costs of detecting, isolating and correcting it increase exponentially compared to if the bug was found at the product development stage);

– reputational damage costs (negative feedback and complaints spread faster than positive information, which can affect the number of potential customers.

Artificial intelligence is becoming the technological foundation for the transition to a proactive model of quality and user experience management. This transition means a change in the approach to quality management – from reactive diagnosis of problems that have arisen, to predicting and preventing problems before they affect users. Modern marketing technology platforms, equipped with advanced artificial intelligence algorithms, are able to analyze huge amounts of behavioral data in real time, processing millions of user interactions at a single point in time. This allows you to not only record the identified problems that led to a negative experience, but also to discover hidden patterns and use predictive analytics to predict future events and bottlenecks in the customer experience that may arise in minutes, hours or days. Machine learning systems can recognize patterns in user behavior that precede rejections, frustrations or platform abandonment.

The evolution of information service quality management models is shown in Fig. 1.

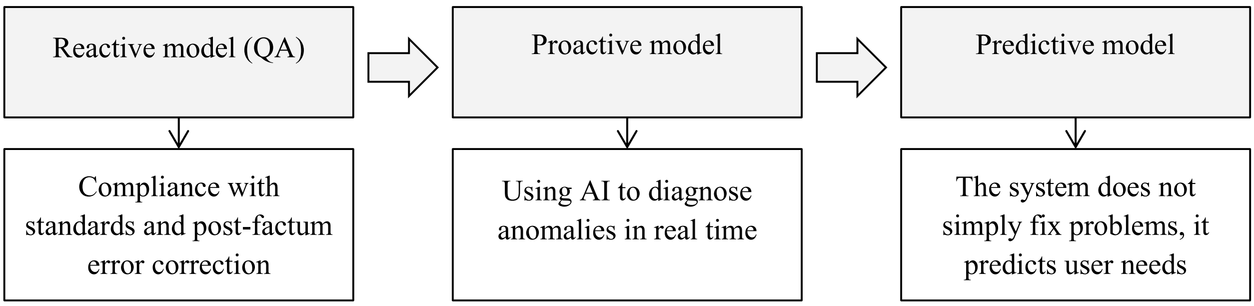

Figure 1. Evolution of information service quality management models
Source: compiled by the authors based on materials (Kyiv-Mohyla Business School, 2025)

One of the most important advances in marketing technology, web analytics, and quality assurance is the ability of artificial intelligence algorithms to automatically detect and classify "frustration signals." "Frustration signals" are implicit behavioral markers that indicate that a user is experiencing difficulty, confusion, frustration, anger, or disorientation while interacting with a digital product, website, or mobile application. Unlike traditional feedback methods that require users to actively complain, these signals are captured automatically, without explicit user intervention (Morten, Hertzum, Kasper, Hornbæk, 2023).

Frustration signals are objective, measurable behavioral patterns that indicate user discomfort. Often, users who are dissatisfied with a product do not share their complaints about their poor experience. As a result, most user experience problems remain invisible to companies if they rely only on explicit feedback. Frustration signals fill this critical gap, allowing companies to identify these problems. This point is especially critical in the context of e-commerce and digital services, where users are one click away from a competitor. When a user closes their browser out of frustration, instead of reporting the problem, it means a lost opportunity to diagnose and resolve the problem, and most importantly, a lost customer.

AI algorithms recognize several well-defined categories of frustration signals, each of which signals different types of problems in the user experience: Rage clicks, Dead clicks, Error Clicks, Mouse thrashing. Rage clicks are a behavioral pattern where a user repeatedly and rapidly clicks on a certain interface element within a short period of time. Algorithms on platforms such as FullStory, Hotjar, and Datadog identify this as a series of clicks (e.g., more than three clicks) within a radius of a few pixels in less than 2 seconds (The FullStory Team, 2024).

The psychology of rage clicks correlates with the physical reaction to a technical failure. In the digital environment, it usually indicates:

– technical lag, when the server does not respond instantly and the interface does not provide visual feedback;

– false affordances, when an interface element looks like an interactive object, but is a static image;

– hidden errors, when there is an error in the console that the user cannot see, but feels due to the lack of response from the site (The FullStory Team, 2022).

For businesses, ignoring rage clicks is costly. In retail, an increase in rage clicks directly correlates with an increase in the number of exits from the site and abandoned carts (Jackie, Ziznewski, 2024).

Table 1 provides a comparative overview of behavioral analytics tools, categorized by availability model and application specifics.

Table 1

Comparison of leading behavioral analytics tools

Company	Tool / Technology	Pain Point
Microsoft Clarity	Free (completely, without traffic restrictions)	Ideal for startups and quick analysis of Rage Clicks without a budget. Allows you to instantly see "dead zones" and JavaScript errors through integration with Google Analytics
Hotjar	Freemium (there is a free plan for small websites)	The best choice for those who want to combine click visualization with direct feedback (surveys) from users to understand the context of behavior
Contentsquare	Paid (enterprise solution)	Recommended for large e-commerce and retail businesses. Provides in-depth Zoning Analysis (financial attribution of each element) and automatic frustration level assessment
FullStory	Paid (trial version / enterprise)	Ideal for deep technical debugging. Combines heat maps with detailed session logs, allowing you to find and fix "unknown unknowns" (hidden logic errors)
VWO / Crazy Egg	Paid (trial version)	Recommended for teams that focus on A/B testing. It allows you not only to see clicks, but also to immediately test hypotheses about interface changes

Source: compiled by the authors

In addition to rage clicks, AI recognizes more subtle nuances of negative experiences. Dead clicks are clicks on elements that do not cause any change in the structure of the page, which the user intuitively considers interactive. This often indicates a violation of the user's mental model, which expects text or images to be links, when in fact they are not (Sophie, Grigoryan, 2025). Error clicks are clicks that immediately precede JavaScript errors, console errors, or server errors. Unlike dead clicks, error clicks indicate a technical disruption, not a user experience problem. Mouse thrashing is rapid, erratic mouse movements that often accompany moments of cognitive overload. Algorithms interpret this as a sign that the user is lost in navigation or frustrated by expectations (The FullStory Team, 2024).

Figure 2 presents the results of the analysis of behavioral patterns of web resource visitors using click-tracking technology. The visualization is made in the format of a heat map, where spectral coding (from cold blue to hot red shades) reflects the density of user interaction with individual interface elements. Red zones indicate areas with the maximum concentration of clicks (high CTR), while blue ones indicate episodic interaction.

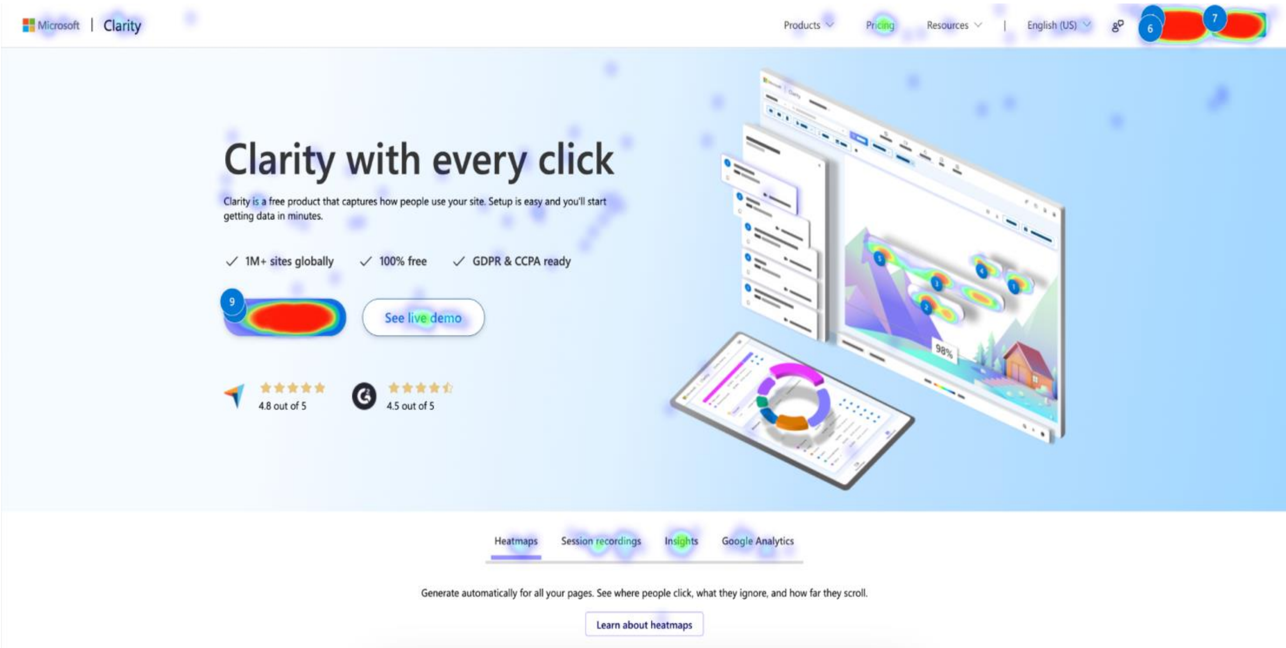

Figure 2. Visualization of the distribution of user activity on the landing page using heat maps using the example of the Microsoft Clarity service

Source: designed by the authors based on (Clarity Staff. How to Use Heatmaps in Microsoft Clarity, 2024)

Analysis of the distribution of "hot zones" allows us to assess the effectiveness of the placement of call to action (CTA) elements. As can be seen from Figure 2, the highest conversion weight is in zone 9, which corresponds to the main registration button located in the visible part of the screen ("above the fold"). The high interaction temperature in this area confirms the hypothesis that contrasting visual highlighting and central placement of the CTA element are key factors in directing the user's path to the target action.

There is also high activity in the upper right corner of the page (zones 6 and 7), which correspond to the functional login and registration buttons. This indicates established mental models of users who intuitively look for authorization elements in a familiar location. At the same time, it is worth noting less activity around the "See live demo" button compared to the main registration button. This distribution of attention indicates that the audience of this resource is more focused on quickly starting to work with the product (direct conversion) than on familiarizing themselves with demonstration materials.

The presented analytics demonstrate the practical application of marketing technologies to manage the quality of a digital product: the data revealed allows you to optimize the page structure, eliminate distractions and maximize conversion by focusing on priority business goals. Identifying these signals allows development teams and UX designers to receive instant notifications about specific issues with the quality of the product. They can review session recordings that demonstrate frustration and proactively fix the problem (e.g. fix a broken button, improve navigation) before the user even contacts support. This turns analytics into an effective instrument of technical QA, putting proactive management into practice.

According to DesignRush, improving UX can increase conversions by up to 400%, and every 1% increase in user retention can lead to a 25-95% increase in profits. This demonstrates that proactive quality management through the detection of frustration signals is not just a quality assurance technique, but a strategic investment in company growth (Frosina, Stojchevska, 2025).

A striking example of the effectiveness of this approach is the study of Endeavour Group, a leader in the beverage retail and hospitality business based in Australia. Using a user experience analysis platform, the company was able to automate the identification of problem areas. By implementing rage clicks monitoring and session replay analysis, the team identified specific problems with the mobile ordering interface. Optimizing the user interface led to a 27% reduction in rage clicks and an increase in the number of items added to the cart by 13% (Kailey, Boucher, 2025).

In a world of global digital platforms, where the scale and speed of change exceed human perception, the only effective response to this challenge has been the implementation of automated anomaly detection systems based on machine learning. When the ecosystem processes millions of transactions per minute, traditional monitoring methods that rely on static thresholds demonstrate their complete inefficiency. They generate a large number of false positives due to natural, cyclical fluctuations in traffic or ignore critical problems if the failure occurs during a period of low activity, when absolute error rates do not reach alarming values.

In this context, artificial intelligence provides a transition from rigid deterministic rules to flexible probabilistic models. Using advanced time series analysis and unsupervised learning algorithms, such systems create a "dynamic baseline" of normal behavior for each business metric in real time. This allows you to detect not only infrastructure failures, but also so-called "unknown anomalies" – hidden defects in business logic that do not cause system errors, but block the user experience (a sharp decrease in conversion at the checkout stage due to a browser version update). This ability of AI to detect the slightest deviations in behavior models before they become widespread is the basis of modern proactive understanding of product quality.

For example, uVitals, Uber's intelligent immunity platform, manages one of the most complex logistics systems in the world. A failure in any part of this ecosystem (for example, problems with driver payments in a particular city) can have critical consequences. Uber engineers developed the uVitals system, which uses unsupervised learning to monitor thousands of business metrics in real time (Uber, 2023). uVitals works as follows:

– forecasting normal conditions (the system uses historical data taking into account seasonality, time of day, holidays, etc. to build a model of expected metric behavior);

– dynamic thresholds (instead of static rules, uVitals dynamically calculates "confidence" intervals. If the number of orders or waiting time goes outside this "corridor", the system records an anomaly);

– contextualization (the system automatically checks whether the decrease in productivity is associated with known factors (for example, a national holiday), reducing the number of false positives).

This allows Uber to detect "silent" failures that do not bring down servers, but can block certain functions at certain moments of overload (for example, customer verification or profile editing). Product quality trends in 2025 – their relevance. Users perceive a product as "quality" if it meets their needs and adapts to them in real time. The role of artificial intelligence in this process goes beyond the traditional diagnosis of problems and negative scenarios. In the context of creative industries and digital marketing, AI has evolved into a powerful creative technology aimed at creating a positive, refined and individualized experience for each user. The highest form of manifestation of the quality of an information service and a digital product is hyper-personalization.

Hyper-personalization involves adapting a product, content, and interface to the needs and context of a specific user in real time, using advanced machine learning algorithms that constantly analyze and adjust every interaction. Unlike basic personalization, which offers the same version of content to several thousand users with similar behavior, hyper-personalization creates a unique experience for each individual. Quality is not a universal standard that can be applied equally to everyone. It becomes personified and contextual. Marketing trends in 2025 clearly indicate that consumers actively expect personalized experiences tailored specifically to them. In response, the fundamental principles of brand interaction with their audience are changing.

According to research, 75% of consumers are more likely to make a purchase from brands that provide personalized content (Kyiv-Mohyla Business School, 2025). This indicates that personalization has become an expectation. Brands that do not adapt to these demands risk losing their competitive position in a dynamic market. Moreover, personalized interactions directly affect conversion rates, customer retention, and long-term lifetime value. Users are more likely to make repeat purchases when they feel that the brand truly understands their needs and offers relevant solutions.

AI is the only technology capable of providing personalization at the required scale – from several hundred to millions of users simultaneously. This is achieved thanks to a complex architecture of machine learning algorithms working in synergy. Machine learning algorithms analyze multidimensional data sets:

– user behavior (every click, scroll, time spent on each page, navigation path through the platform);

– interaction history (previous purchases, viewed products, added to the cart and later removed);

– explicit and implicit preferences (from explicitly specified filtering parameters to implicit signals coming from behavioral patterns);

– contextual factors (time of day, device, geographic location, weather, seasonality, the device from which the user enters).

Based on this analysis, AI allows:

– dynamically adapt content that best matches the interests and needs of the viewer. Real-time recommendation algorithms process hundreds of possible content options and offer exactly what is most likely to interest the user at that moment in time. This is done based on learning on huge sets of historical data;

– personalize the interface (UI/UX), offering the most necessary functions based on the user's previous behavior. For example, if a user often uses a price filter, it appears at the top of the page specifically for him. If another user mainly searches by brand, the system rearranges the interface elements specifically for his needs. This requires the development of flexible, modular design systems that can dynamically change their location and visibility of elements;

– use generative AI to automatically create unique content. Instead of storing ready-made text descriptions, headlines or images in a database, generative models create content on the fly. For one user, the system can formulate a product description with an emphasis on its practicality, for another – on aesthetic qualities, for a third – on environmental friendliness. Generative algorithms can also adapt the tone, style and complexity of language depending on the demographic characteristics and language preferences of the user (0222 Digital Agency, 2025).

Hyper-personalization operates at the intersection of several technological levels. At the level of data collection and processing, systems receive signals from browsers, mobile applications and other sensors in real time. Data is sent to data warehouses and data lakes, where it is normalized, cleaned and prepared for analysis.

At the machine learning level, collaborative filtering compares a user's behavior to millions of similar patterns of behavior from other users to find similar items or content. Content filtering analyzes the attributes of the content itself (tags, categories, descriptive features) and matches them to the user's profile. Hybrid models combine both approaches for greater accuracy. At the experience personalization level, the system makes decisions about content presentation, sequencing, tonality, and device based on all previous levels. These decisions are made in milliseconds.

The Duolingo educational platform is a prime example of using artificial intelligence to ensure the quality of the learning process and user retention. Their system, called "Birdbrain," uses sophisticated algorithms to personalize each lesson:

– adaptive difficulty. Birdbrain analyzes the user's error history and dynamically selects exercises. If the user often makes mistakes in a certain area of learning, the system provides less difficult tasks for reinforcement. If the user answers too easily, the system increases the difficulty. Quality is measured by finding a balance in the "zone of closest relevance";

– retention optimization. Duolingo uses multi-agent AI to choose the optimal time and text notifications. This is not just spam, but a calculated psychological impact aimed at maintaining attention to the service. Thanks to this, Duolingo achieves phenomenal retention rates – over 55% of users return to study the next day.

An interesting example of personalizing search and trust is Airbnb, a global two-way marketplace connecting over 4 million homeowners with a billion guests, which faces a unique challenge of trust and relevance. The company uses over 100 machine learning models for search and ranking alone, transforming the process of choosing a home from simple filtering to a deeply personalized experience through:

– two-way matching. Unlike hotels, where bookings are guaranteed, Airbnb hosts can refuse. Therefore, the ranking algorithm takes into account not only the guest's preferences (price, location, style), but also the probability that a particular host will accept a booking from that guest (Host acceptance probability). This reduces the number of rejections, which is a critical indicator of service quality for both parties and saves users time;

– personalized categories (Visual categorization). Airbnb uses Computer vision to deeply analyze millions of photos of homes. Neural networks automatically classify properties by style and features (for example, recognizing “amazing pools,” “Scandinavian design,” or the presence of a workspace), even if the owner did not indicate this in the description. This allows users to be shown homes that emotionally resonate with their aesthetic taste and travel purpose.

Figure 3 demonstrates a closed personalization loop in which artificial intelligence analyzes collected data about user behavior to instantly adapt the interface and content to their needs. Improved experiences drive customer return (Retention) and growth in their value (LTV), which generates new data for continuous improvement of the algorithm.

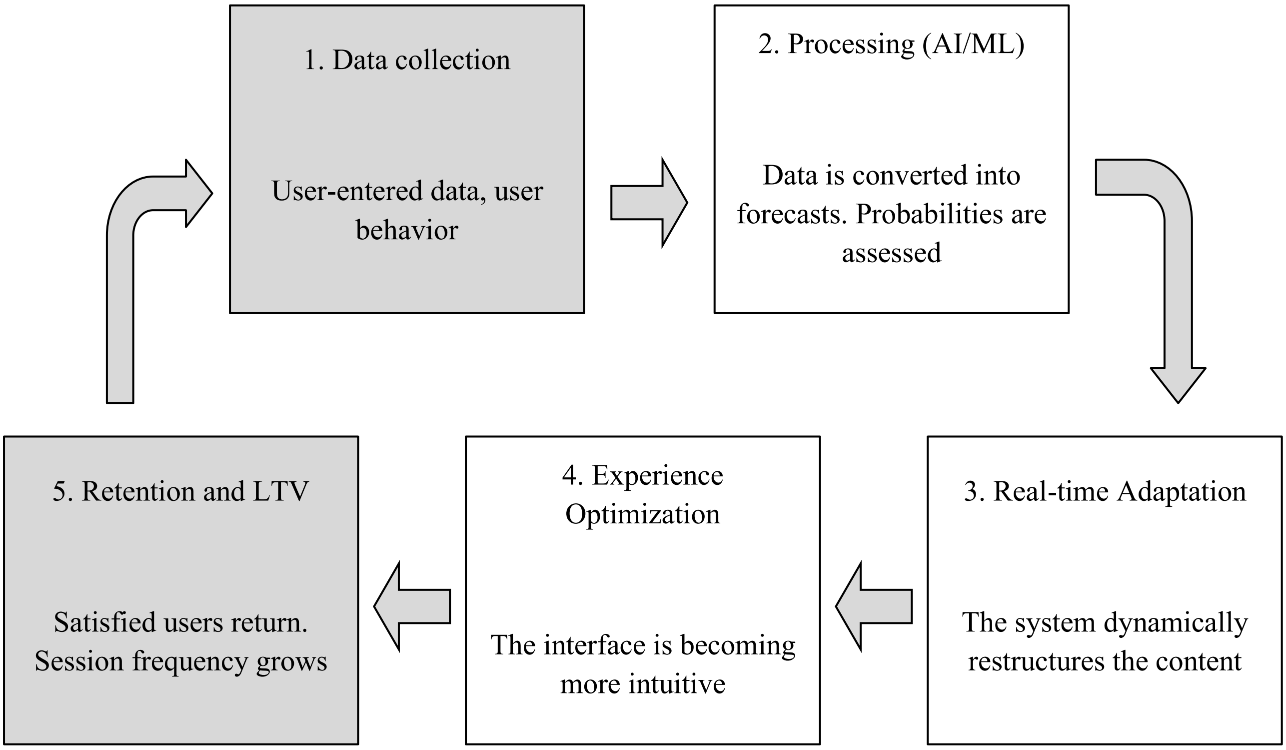

Figure 3. Personalization Feedback Loop

Source: Compiled by the authors based on (Michele, Morales, 2025)

The world leader in e-commerce, Amazon, is tackling the “paradox of choice” and information overload with Rufus, an AI-powered generative assistant integrated directly into its mobile shopping app. Rufus is not just a chatbot, but an expert system trained to work with Amazon’s entire product catalog, customer reviews, community Q&A, and information from the open web. Drawing on this vast knowledge base, the assistant can interpret vague intent, clarify user goals, and refine queries step by step, acting more like an experienced sales consultant than a traditional search bar. It allows users to engage in natural dialogue with complex, contextual questions that would previously require hours of independent research (e.g., “What are the best sneakers for beginners on asphalt?” or “Compare drip and pod coffee makers for a small kitchen”), while instantly narrowing down thousands of options to a convenient and relevant shortlist. Amazon data shows that customers who interact with Rufus are 60% more likely to make a purchase, demonstrating a significant increase in conversions that is attributable to AI-powered decision-making, not just traffic growth. This shows that high-quality, personalized, real-time advice directly impacts business success and reduces cognitive load on the shopper, transforming product search from a routine to a dialogue and helping users feel more confident that they are making informed, optimal choices for their specific context.

Table 2 presents the experiences of global technology leaders, demonstrating which specific AI tools are being used to solve specific quality problems and improve the user experience. It illustrates the direct connection between implementing AI-based solutions and achieving measurable business results, such as increasing customer retention and minimizing financial losses.

Table 2.

Comparative analysis of AI application for quality management

Company	Tool / Technology	Pain Point	AI Solution	Result / Impact on business
Duolingo	Birdbrain AI	Loss of motivation, uneven lesson difficulty	Personalization of exercise difficulty and notification timing	51% increase in DAU, retention rate >55%
Uber	uVitals (based on Michelangelo)	“Silent” technical failures affecting revenue	Real-time detection of anomalies in business metrics	Quick detection of payment/order issues
Revolut	Fraud Detection ML (Breaking the Spell)	Social engineering, APP fraud	Interactive alerts and blocking of suspicious transfers	Prevention of £475 million in fraud in 2023
Endeavour Group	FullStory (Frustration Detection)	Non-obvious UX errors, Rage Clicks	Automatic detection of problem zones through session analysis	27% reduction in Rage Clicks, 13% increase in Add to Cart
Airbnb	Search Ranking ML, Computer Vision	The complexity of choosing a property, mistrust between the parties to the agreement	Personalized two-way matching, classification of properties by photo	Reduction in booking cancellations, increased trust

Source: compiled by the authors based on (The Fullstory Team, 2025; Uber, 2023; Revolut, 2024, Sakshi, Jonwal, 2025)

Conclusions and perspectives of further research. An analysis of the current market situation shows that the traditional reactive QA model, focused exclusively on correcting technical errors, is economically unprofitable in the context of the “experience economy.” The phenomenon of “silent churn,” where 96% of dissatisfied customers leave the service silently, is forcing businesses to move to proactive strategies. The quality of a digital product today is determined not by its compliance with specifications, but by the system's ability to anticipate and eliminate user frustration before it is even realized.

The use of machine learning algorithms to detect “signals of frustration” (Rage clicks, Dead clicks) has made it possible to digitize the user's emotional state, transforming subjective feelings into accurate engineering data. As practical experience shows, this approach allows you to identify non-obvious barriers in the interface (UX friction) in real time. The role of analytics is changing from passive reporting to an active diagnostic tool that affects conversion retention and reduces the load on support.

For global platforms of Uber's scale, automated anomaly detection has become a standard of reliability. The transition to dynamic probabilistic models allows for the detection of specific business logic failures that do not cause system crashes but block revenue. The ability of AI to form an adaptive “norm” of metric behavior minimizes the risk of missing critical incidents. The cases of Duolingo, Airbnb, and Amazon Rufus confirm that in the age of AI, the concept of quality is inextricably linked to relevance. Hyper-personalization is becoming a functional requirement: a product that does not adapt to the user's context is perceived as defective. Intelligent algorithms that tailor content and search results are becoming the main driver of customer retention and LTV growth.

The theoretical significance of the results obtained is determined by the disclosure of the process of transforming the role of web analytics from a passive reporting tool to a proactive diagnostic system. The theoretical basis for the need for a synergistic combination of marketing technologies and quality assurance (QA) engineering practices has been established, and the effectiveness of using dynamic AI models to form adaptive metric behavior has been proven. The practical significance of the results lies in the possibility of applying the developed approaches by IT companies to identify non-obvious barriers in the interface in real time. As the experience of global companies proves, the implementation of automated algorithms for anomaly detection and content personalization prevents the loss of revenue from business logic failures and directly affects customer retention and the growth of their lifetime value (LTV).

The scientific novelty of the study lies in the conceptual justification of hyper-personalization and relevance as integral components of digital product quality in the AI era. The possibility of digitizing the user's emotional state through the detection of "signals of frustration" has been proven, which transforms subjective feelings into accurate engineering data for predictive diagnostics.

Prospects for further research lie in studying the development of a "generative user interface" (Generative UI) based on multimodal AI models to create ecosystems that can dynamically adapt to each client. Special attention should be paid to researching the ethical aspects of continuous analysis of user behavior patterns and the impact of Emotion AI on the objectivity of customer experience assessment.

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