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«ІНФОРМАЦІЙНІ ТЕХНОЛОГІЇ І АВТОМАТИЗАЦІЯ – 2025»

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ANALYSIS OF INTELLECTUAL DATA ANALYSIS METHODS FOR EVALUATING USER BEHAVIOUR

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Analysing user behaviour in the digital environment requires the use of intelligent data analysis. The study proposes a combination of cluster and discriminant analysis for segmentation and prediction of target actions (e.g., purchases) based on interaction metrics.

In today's digital world, companies and developers are faced with a huge flow of information about how users interact with their products – websites, applications, services. These ever-growing volumes of data on clicks, views, purchases and other actions can easily turn into information noise if you don't have effective tools to analyze them. Without a deep understanding of user behavior, it becomes difficult to make informed decisions about product development, content personalization, or marketing strategies, leading to missed opportunities and inefficient use of resources. In such situations, data mining methods become reliable tools for identifying hidden patterns and assessing user behavior.

For a comprehensive analysis and understanding of user behavior in the digital environment, it is important to consider three key aspects: how this behavior can be measured, how it can be conceptually modelled, and what factors influence it. Behavior is measured using a variety of metrics that allow for the quantitative assessment of different aspects of user interaction with a digital product. Behavioral models help to structure the understanding of these interactions, explain existing patterns, or predict future actions. Finally, influencing factors provide the necessary context, explaining why users behave in one way rather than another, considering both their internal characteristics and the features of the external environment.

Key aspects of analysing user behaviour in the digital environment:

Behavior measurement: visitor numbers/traffic; engagement; navigation; conversions; retention; satisfaction/experience;

User behavior models: describing the decision-making process; describing interaction; data-driven; agent-based; profiling;

Factors influencing behavior: internal; external.

User behaviour in the digital environment is a complex, multifaceted and dynamic phenomenon that reflects human interaction with technology. Studying it is key to creating successful digital products. The characteristics of this behaviour, such as purposefulness, measurability, variability and the presence of patterns, make it a suitable object for the application of intelligent data analysis methods.

Since user interaction generates a lot of different information, we will highlight the following potentially important groups of indicators:

session and visit data: traffic sources, visit time, session duration, device type, geographic data, number of pages/screens viewed;

data on interaction with content and functionality: page view sequences (user paths), clicks on interface elements, search usage, form filling, video viewing, time on page, scrolling depth;

conversion action data (if relevant): purchases, registrations, subscriptions, file downloads, other goal completion;

user data (if available and relevant): demographic characteristics, history of previous interactions, user segment (if previously segmented).

This data is typically captured by web analytics systems, internal application logs, or special event tracking systems.

Solving the problem of evaluating user behaviour requires the use of adequate methods of multidimensional statistical analysis capable of processing complex data sets that characterise objects according to many features. This section discusses two classes of such methods, namely cluster and discriminant analysis.

Although these methods solve different problems – cluster analysis aims to reveal the internal structure of data and segment objects without prior information about classes, while discriminant analysis is used to classify objects into predefined groups – they can be effectively combined to achieve the goals of this study. In particular, we plan to use cluster analysis to identify natural segments of users based on their behavioural patterns, and then apply discriminant analysis to build a model that predicts target actions (e.g., purchases) and identifies key behavioural factors that distinguish users.

To visualize and structure this comprehensive approach, it is advisable to construct a conceptual research framework. This diagram will reflect the main stages of analysis, linking specific models that need to be developed to assess user behavior and potential demand with the corresponding methods of intelligent data analysis that will be used to solve them (Table 1).

Table 1. Conceptual diagram of building models for intelligent data analysis

Models / Research tasks	**Intelligent data analysis methods**
M1. Model of user segmentation by behavior patterns (identification of typical user groups)	Cluster analysis (CA): Hierarchical methods (dendrograms, Ward's method) for visual determination of the number of clusters; K-means method for final cluster formation; Calculation of distance measures (Euclidean) to calculate similarity between observations.
M2. Classification model for assessing cluster membership (verification of segmentation accuracy and development of classification rules)	Discriminate analysis (DA): Construction of discriminant functions to separate clusters; Classification of observations according to the discrimination rule; Assessment of classification accuracy (error matrix, Wilks' lambda)
M3. Analysis of factors influencing behavioral membership (interpretation of clusters and discriminant functions)	Descriptive statistics (for profiling clusters obtained in M1). Analysis of discriminant function coefficients (from M2) to determine the importance of features.

The key task of the practical part is to evaluate their behavior in terms of predicting specific outcomes. In particular, the goal is to develop a model that will allow, based on data about user interaction with a digital product (collected behavior metrics), to assess the probability of achieving target actions, such as making a purchase or leaving positive feedback, as well as potentially classifying users by level of satisfaction.

A comparative analysis revealed fundamental differences between cluster analysis and discrimination analysis. Cluster analysis, as an unsupervised learning method, aims to reveal the internal structure of data and form groups (clusters) of objects based on their similarity, regardless of any external criteria or target variables. Although it can be useful for exploratory analysis and identifying unknown user segments, it does not provide direct tools for solving classification or prediction problems for predefined categories.

In contrast, discriminant analysis is a supervised learning method, the main purpose of which is to develop rules for classifying objects into known groups. Direct alignment with goals: discriminant analysis allows you to build a model that, based on behavioral predictors (number of views, session time, functions used, etc.) will classify users into target categories (‘bought’/‘did not buy’, ‘left positive feedback’/‘did not leave’, ‘highly satisfied’/‘low satisfaction’).

Predictive power. The discriminant function (or functions) can be used to predict the behavior of new users, which has high practical value for business (for example, for targeting marketing campaigns or proactive work with customer support).

Interpretation of influencing factors. Discriminate analysis not only classifies but also allows you to evaluate the contribution of each behavioral characteristic to the separation of groups. This makes it possible to understand which aspects of behavior are the most significant indicators of the likelihood of purchase, satisfaction or leaving positive feedback.

Thus, the application of intelligent data analysis methods to assess and predict key aspects of user behavior (probability of purchase, leaving positive feedback), the optimal solution would be to combine these two models.

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MAPPING ONLINE BEHAVIOR OF UKRAINIAN STUDENTS THROUGH K-MEANS CLUSTERING

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Abstract. *The paper explores the phenomenon of Internet dependency among Ukrainian youth, emphasizing behavioral tendencies, emotional aspects, and the role of digital habits in shaping daily life. The study combines theoretical research, online data collection, and statistical clustering to identify distinct user profiles that reflect varying degrees of Internet engagement and addiction risk.*

***Keywords**: Internet addiction, digital behavior, Ukrainian youth, clustering analysis, K-means method, online survey, Google Forms, social media, digital wellbeing.*

Introduction

Over the past decade, the Internet has evolved from a communication tool into an essential part of everyday life. According to the *Digital 2024* global report, more than 5.5 billion people—about two-thirds of the world’s population—use the Internet daily, spending an average of 6.5 hours online. For many, online activity is an integral part of work, study, entertainment, and social interaction. However, the fine line between productive use and dependency often becomes blurred, especially among young users who spend a significant portion of their time in digital environments.

Theoretical Background