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USING CLUSTER ANALYSIS TO STUDY THE CHARACTERISTICS OF MICRO-FREIGHT FLOWS OF SHOPPERS

The article presents the results of a study aimed at identifying socio-demographic and behavioral factors influencing people's choice of transport mode during shopping trips. Considering the increasing volume of shopping-related trips and the growing attention to the environmental aspects of urban mobility, the study examines the phenomenon of micro-shopping flows as part of the broader urban freight transport system.

The study is based on an online survey of 479 respondents. Using hierarchical clustering, two main clusters of shoppers were identified. The first cluster consists of middle-aged individuals, predominantly women, who combine active employment with medium-weight purchases (2–5 kg), mostly during daytime hours, and prefer traveling by private car or on foot. The second cluster primarily comprises students who make small purchases (up to 2 kg), more often after 3:00 p.m., often combining public transport and walking.

The results confirm the presence of statistically significant differences between the groups in terms of age, gender, occupation, shopping time, and purchase weight. A clear relationship was found between purchase weight and choice of transport mode: as the weight increases, the likelihood of using a private car rises significantly. Similarly, temporal characteristics influence modal choice — walking predominates in the morning hours, while the share of car and public transport trips increases in the afternoon.

The practical significance of this study lies in providing a scientific basis for developing targeted sustainable transport planning measures aimed at specific user groups. For young people, it is advisable to focus on improving access to public transportation and developing micro-mobility infrastructure. For the working population, effective measures may include incentives to reduce private car use.

Future research prospects are related to modeling the impact of micro-shopping flows on overall urban traffic. Such analysis is important for managing peak loads in the transport system and for developing policies aimed at the environmentally sustainable development of urban transport.

Keywords: shopping trip, cluster analysis, socio-demographics indicators, mode choice, micro freight flows

INTRODUCTION

Despite the growing popularity of online shopping, travel demand for shopping purposes remains a significant component of overall travel demand within urban areas [1, 2].

In recent years, the number of studies on "green purchases" has increased significantly, focusing on the environmental impact of consumer habits [3]. Researchers examine the factors influencing consumers' intention to make environmentally friendly purchases (individual characteristics, cognitive and social factors, product features, and marketing aspects) and assess the potential effects of an increasing share of such purchases [4–6]. "Green purchases" are part of the broader concept of "green behavior" (GB), which refers to private-sphere habits related to everyday environmentally responsible actions — such as household consumption aimed at reducing waste, saving water and energy, prioritizing products with a lower environmental impact, and using reusable goods [7]. Within this broader context, the choice of travel mode is an integral part of GB [8]. If "green purchasing" practices are carried out using a private car, the environmental benefits of such actions are largely offset. Therefore, the choice of transportation mode constitutes an essential component of green behavior overall and is a factor that directly influences the real contribution of "green purchases" to reducing environmental impact.

To effectively respond to new mobility trends and develop a comprehensive planning approach that promotes "soft" modes of transport while preventing undesirable consequences, public authorities need access to information not only on urban freight transport and logistics but also on individual travel patterns and consumer behavior [9]. To design a system of measures that fosters an environmentally sustainable transport system, it is essential to understand which individual and contextual variables influence people's choice of travel mode [10]. Compared to commuting trips, shopping-related trips are more flexible in terms of destination and timing. Therefore, measures that encourage the use of more environmentally friendly transport modes for shopping trips may prove to be more effective [11].

ANALYSIS OF LITERATURE DATA AND FORMULATION OF THE PROBLEM

Recent studies in the field of last-mile logistics have expanded the scope of urban freight transport to include, in addition to actual last-mile delivery, shopping trips made by private cars [12]. Ensuring sustainability in last-mile distribution is a complex challenge due to the growing volume of deliveries combined with strict time requirements [13]. Therefore, a promising direction may be the development of measures aimed at encouraging consumers to switch to more environmentally friendly modes of transport.

Factors influencing users' choice of travel mode in a transport system can be divided into three groups: socio-demographic characteristics, built environment (building density, land-use mix, distance to various facilities, etc.), and attitudes (comfort, convenience, travel satisfaction) [10]. While the scientific literature contains a substantial number of studies on these factors, there are relatively few publications focusing specifically on shopping-related trips. In recent years, researchers have primarily concentrated on examining changes in consumer purchasing behavior associated with the Covid-19 pandemic and/or the growing share of online shopping [1, 14, 15]. However, most studies focus on trips in general or commuting trips [10].

According to the study presented in [16], as population density and the density of shopping locations decrease, the frequency of shopping trips made by car increases.

In [17], based on the analysis of survey results conducted in Munich, Germany, purchasers were divided into six latent classes according to their shopping behavior (including the frequency of offline and online purchases and the mode of transport used for offline shopping). These studies indicate that the groups most inclined to use a car for shopping trips are employed individuals with high income, those with children and access to a private car, as well as residents of less dense residential areas.

In [18], consumer shopping behavior was analyzed based on survey data from Japanese respondents. According to the published results, the choice of travel mode for shopping trips is influenced by employment status (working respondents typically choose the car, while non-working respondents prefer cycling or walking), the distance to the shopping location, and the duration of stay at the destination (those who walked spent the least time shopping, while those who arrived by car spent the most).

According to the studies presented in [19], the frequency of shopping trips made by car is influenced more by habit than by socio-demographic characteristics (the research was based on survey data collected in Sweden). The authors recommend that when developing measures aimed at changing urban travel behavior, special attention should be given to alternatives that prevent and/or reduce the formation of strong habitual patterns.

RESEARCH QUESTIONS

Based on the literature review, the following research questions are formulated:

- -RQ1. What factors influence consumer purchasing behavior, and what typical groups of shoppers can be identified?
- -RQ2. How can sustainable urban transport policies be adapted to meet the needs of specific groups of shoppers?

RESEARCH RESULT

Data collection procedure and general characteristics of the survey results

To collect data, an online survey of the population was conducted (the questionnaire was created in Google Forms and distributed via social media). A total of 491 completed questionnaires were collected, of which 479 were retained for further analysis after excluding those containing incomplete or evidently false information. The data gathered through the survey can be divided into the following blocks: socio-demographic and socio-economic characteristics of the respondents; general behavior during the purchase of food and non-food products (frequency, place of purchase, typical mode of transport for shopping trips); and information regarding the most recent offline purchase (time, place, amount spent, and mode of transport).

The sample consisted of 63% women. The survey mainly involved young people, with 83% of respondents under the age of 40. The distribution of the sample by average monthly household income was as follows: up to UAH 14,000 — 29%, UAH 14,000–20,000 — 16%, UAH 20,000–30,000 — 16%, UAH 30,000–40,000 — 13%, and over UAH 40,000 — 26%. Employed individuals accounted for 45% of respondents, students for 46%, and the remaining respondents were unemployed (6%) or retired (3%). Among the respondents, 53% (253 individuals) had lived in a large city (population over 300,000) for at least the past six months, 30% (142 individuals) in a city with a population under 300,000, and 17% (83 individuals) in a rural area.

Place of residence affects the frequency of both food and non-food purchases, although the difference is more pronounced for non-food items (Fig. 1).

a) b)

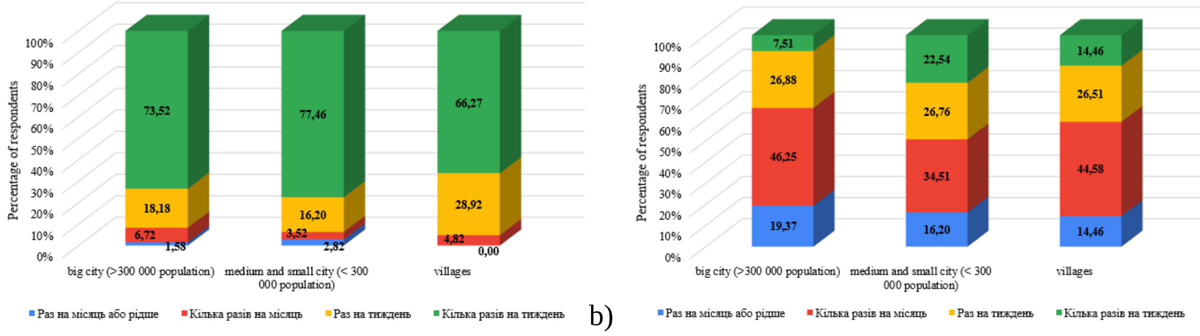

Fig. 1. Distribution of purchases by frequency: a) food products; b) non-food products

Most respondents, regardless of their place of residence, purchase food products several times a week. For rural residents, this figure is slightly lower, with a larger share of purchases occurring once a week. Less than 9% of respondents buy food products less frequently than weekly. For non-food purchases, the differences are more pronounced. The share of respondents making such purchases once a week is almost the same across different residential locations, with only a small variation in the proportion of those purchasing non-food items no more than once a month (15–20%). However, several times a week, 7.5% of residents of large cities make non-food purchases, compared to 22.5% of residents of smaller cities.

Small-volume purchases prevail: 47% of respondents indicated that their most recent purchase weighed less than 2 kg, while 39% reported a weight between 2 and 5 kg. Moreover, 83% of respondents stated that a purchase of this size is typical for them.

The distribution of responses regarding the choice of transport mode for shopping trips is shown in Fig. 2.

a) b)

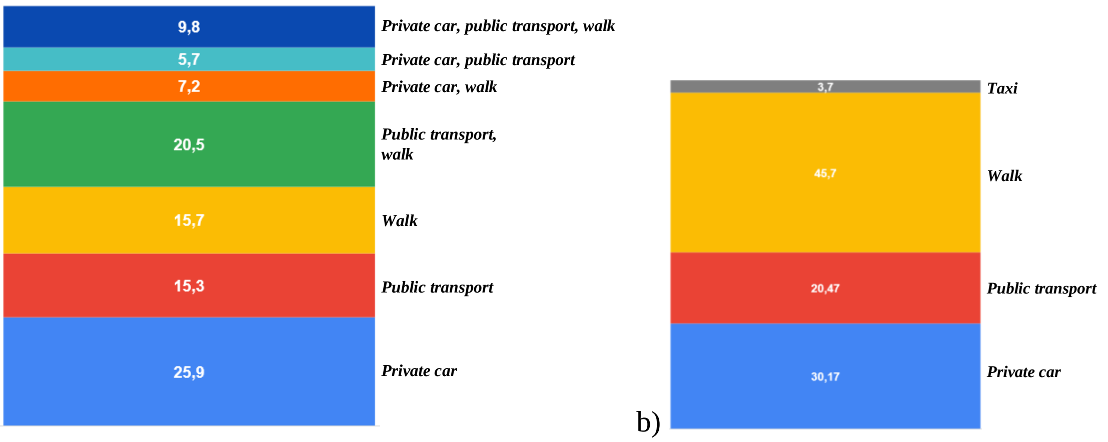

Fig. 2. Mode choice for shopping trips: a) usually; b) during the most recent purchase

Approximately 26% of respondents usually choose a car for shopping trips, while around 23% indicated it as one of the alternatives they use regularly. For public transport, these figures are 15% and 36%, respectively. Overall, transport-based trips account for 41% of all shopping trips, with an additional 43% regularly combining them with walking. Fifty-one percent of respondents reported using some form of transport during their most recent purchase.

Clustering procedure

Among the methods for assessing travel behavior in urban areas, regression models and machine learning techniques are the most popular [10, 20]. Cluster analysis, as one of the machine learning algorithms, is an effective method for dividing datasets into subgroups characterized by distinct differences. Conducting cluster analysis involves the following main steps [21]:

-normalization and standardization of input data;

- dimensionality reduction (excluding data from the sample that do not influence the clustering results);

-cluster identification (based on distance to a cluster centroid, dissimilarity and linkage between groups of observations or density);

-evaluation of results (assessing the reliability of clustering for a given number of clusters).

If the input dataset contains different types of data (numerical, categorical, binary, and multiple-choice), they need to be represented using a common standard. Several methods can be used for encoding:

-One-Hot Encoding is applied to features with a single choice among multiple categories (e.g., gender, time of purchase). This approach helps avoid false assumptions about the order or equidistance between categories, which is particularly important for models sensitive to numerical values (such as decision trees or logistic regression).

-Multi-Hot Encoding is applied to fields where respondents could select multiple options simultaneously (e.g., modes of transport to the shopping location). Each category is transformed into a separate binary variable indicating the presence or absence of the corresponding feature.

-Ordinal Encoding is used for ordered variables, such as income level or purchase weight. Preserving the order allows the model to account for monotonic relationships, which is appropriate when the values have a logical progression (e.g., «less than 2 kg» < «2–5 kg» < 5–10 kg»).

As a result of the preprocessing, a complete set of features suitable for use in clustering and classification algorithms was created. Each row in the table represents an individual respondent, and each column corresponds to a standardized, encoded feature.

Clustering of respondents based on the mode of transport they most frequently use for shopping trips

The study employed hierarchical clustering with dendrogram construction using Ward's method. The proximity matrix was calculated using the normalized Manhattan distance metric. The clustering process workflow in Orange software is shown in Fig. 3. To determine the importance of variables in the clustering procedure, the Rank function was first applied to the target variable, "mode of transport for shopping trips," and the variables that most influenced the choice of transport mode were selected.

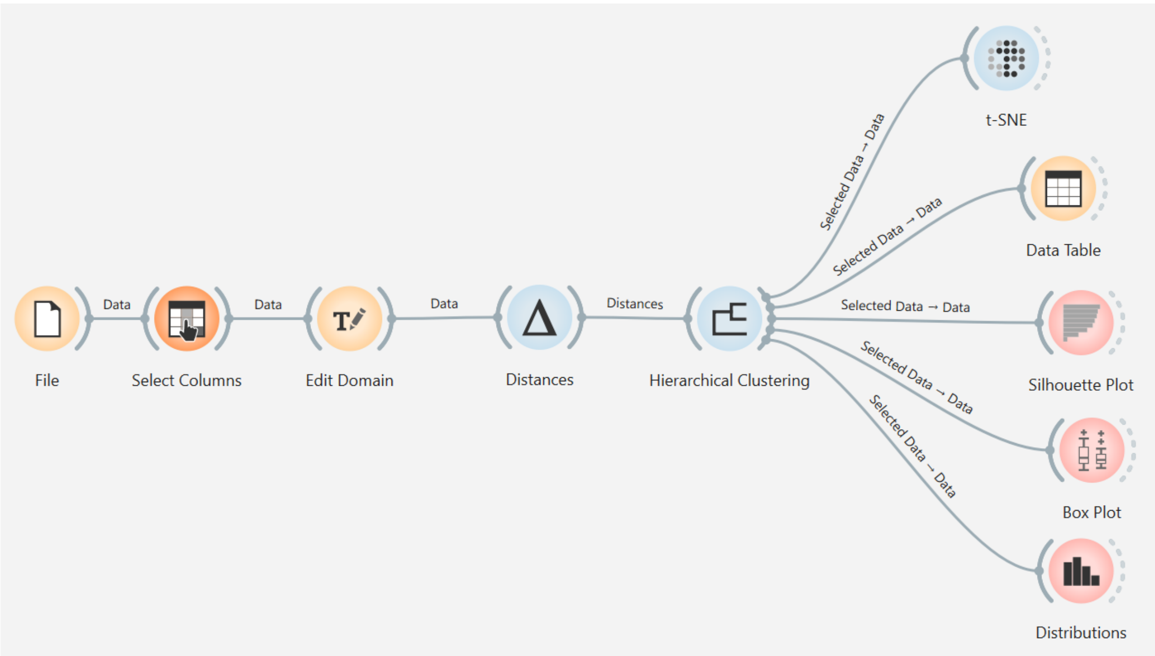

Fig. 3. Hierarchical clustering procedure using Orange software

First, six factors were selected using the Rank function:

- age;
- gender;
- type of employment;
- household size;
- time of the trip;
- purchase weight.

The optimal number of clusters was determined based on the silhouette score values (Table 1).

Table 1. Selection of the optimal number of clusters

Total number of clusters	Weighted average silhouette score	Silhouette score values for each cluster				
		C1	C2	C3	C4	C5
5	0.24	0.564	0.413	0.084	0.199	0.119

4	0.40	0.564	0.413	0.133	0.455	–
3	0.38	0.382	0.142	0.455	–	–
2	0.63	0.498	0.702	–	–	–

The silhouette score reflects the level of cohesion within a cluster. Its values range from -1 to +1, with values closer to 1 indicating that an object fits well within its cluster [22]. For the selected set of factors, the best results were obtained by dividing the sample into two clusters.

Members of the first cluster primarily make shopping trips by private car (48%) or on foot (33.7%). This group consists mainly of middle-aged working individuals, predominantly women. The second cluster mainly comprises students who prefer using a private car (41%) or public transport (32.4%) for their trips. A more detailed characterization of the resulting clusters is presented in Table 2.

Table 2. Clustering parameters and factors considered in the cluster division

Variable	Value type	Mean value and dispersion (for a numerical variable)	Percentage distribution (for a categorical variable)	Estimate
Cluster C1				
Age	Numeric	44,75±10,1		Student`s t = 22,19 p=0,000
Household size	Numeric	3,48±1,2		Student`s t = 1,51 p=0,133
Gender	Categorical		84,3% – female	χ^2 = 27,05 p=0,000
Type of employment	Categorical		83,15% – employed population	χ^2 = 117,69 p=0,000
Time of the trip	Categorical		21,35% – 9:00 – 12:00 30,34% – 12:00 – 15:00 22,3% – 15:00 – 18:00 22,5% – after 18:00	χ^2 = 11,08 p=0,050
Purchase weight	Categorical		17,3% – purchases weighing up to 2 kg 56,8% – purchases weighing 2–5 kg 17,3% – purchases weighing 5–10 kg	χ^2 = 28,67 p=0,000
Cluster C2				
Age	Numeric	20,2±3,8		Student`s t = 22,19 p=0,000
Household size	Numeric	3,24±1,3		Student`s t = 1,51 p=0,133
Gender	Categorical		50% – female	χ^2 = 27,05 p=0,000
Type of employment	Categorical		69,3% – students	χ^2 = 117,69 p=0,000
Time of the trip	Categorical		14,77% – 9:00 – 12:00 22,7% – 12:00 – 15:00 37,5% – 15:00 – 18:00 23,3% – after 18:00	χ^2 = 11,08 p=0,050
Purchase weight	Categorical		53,9% – purchases weighing up to 2 kg 34,2% – purchases weighing 2–5 kg 9,4% – purchases weighing 5–10 kg	χ^2 = 28,67 p=0,000

The p-value for the variable "household size" is greater than the critical value of 0.05; therefore, the clustering was performed without taking this factor into account. The calculations presented in Table 3 confirm the appropriateness of this step, as the weighted average silhouette score increases.

Table 3. Selection of the optimal number of clusters

Total number of clusters	Weighted average silhouette score	Silhouette score values for each cluster				
		C1	C2	C3	C4	C5
5	0,27	0,657	0,423	0,100	0,318	0,112
4	0,44	0,657	0,423	0,162	0,526	–
3	0,42	0,393	0,170	0,526	–	–
2	0,67	0,522	0,739	–	–	–

Members of the first cluster mainly make medium-weight purchases (2–5 kg), with more than half of the trips occurring before 3:00 p.m. (55%). In the second cluster, purchases weighing up to 2 kg prevail (54%), and shopping trips are shifted toward the afternoon hours (after 3:00 p.m.) – 61% of purchases.

Separate graphical dependencies were constructed between the time of purchase and choice of transport mode, as well as between purchase weight and choice of transport mode (Fig. 4 and Fig. 5).

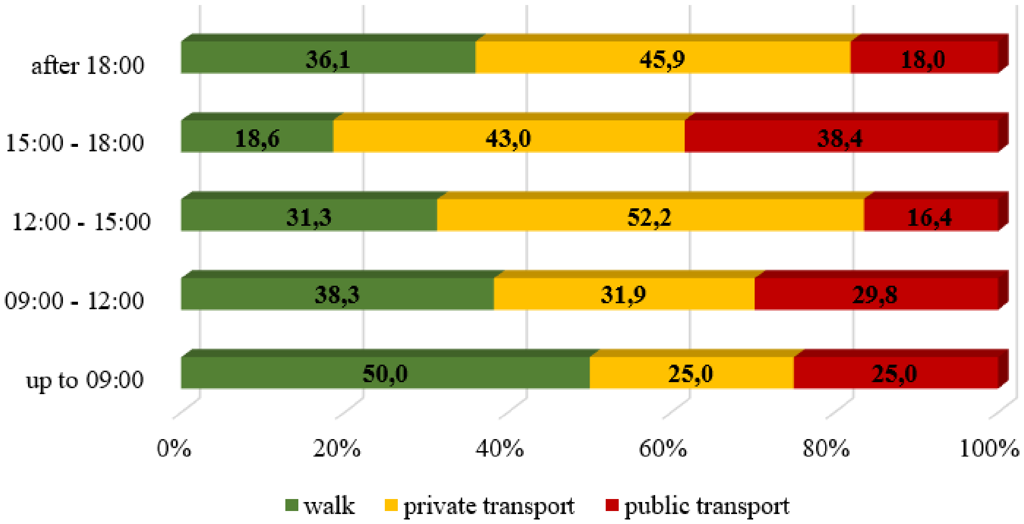

Fig. 4. The impact of purchase time on the mode choice

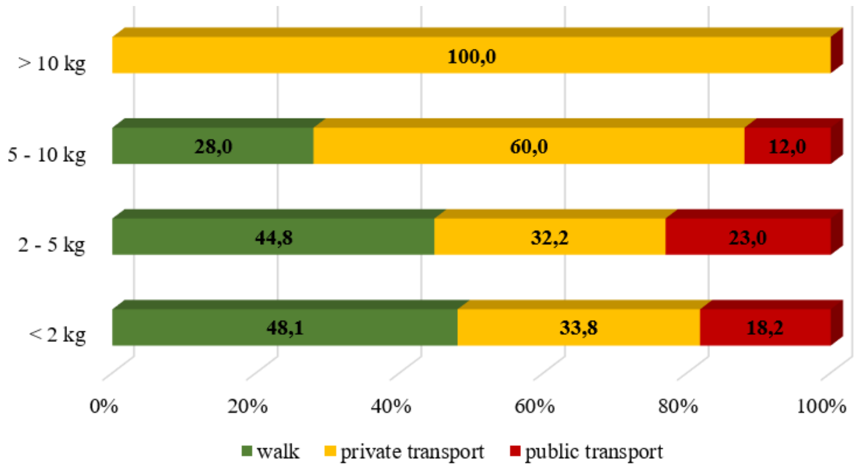

Fig. 5. The impact of purchase weight on the mode choice

The highest share of walking trips occurs during morning shopping (50% for purchases before 9:00 a.m. and 38% for purchases between 9:00 a.m. and 12:00 p.m.). After 12:00 p.m., the overall use of transport, particularly private vehicles, increases. Public transport is most actively used during the afternoon hours, with over 38% of respondents utilizing it for shopping trips between 3:00 p.m. and 6:00 p.m.

The relationship between the choice of transport mode and purchase weight is even more pronounced. For the smallest weight category (< 2 kg), walking is the predominant mode of transportation (48%). As purchase weight increases, the use of transport also rises: for medium-weight purchases, the share of walking slightly decreases in favor of public transport, while for purchases over 5 kg, the share of trips made by private car sharply increases, reaching nearly 100% for purchases weighing more than 10 kg. This is supported by other studies, which indicate that a larger shopping list or visiting multiple stores in a single shopping trip significantly increases the likelihood of using a private car [23].

DISCUSSION OF THE RESULTS OF THE STUDY AND SUMMARY

The conducted study made it possible to identify the key socio-demographic and behavioral factors that determine consumers' choice of transport mode for shopping trips. The application of cluster analysis allowed the identification of two groups of respondents differing in age, gender, occupation, as well as the weight and timing of their purchases.

Middle-aged respondents, predominantly women with active employment, prefer to use private cars or walk for shopping trips. Their purchases are typically of medium weight and occur throughout the day, with slightly higher activity between 12:00 and 3:00 p.m., possibly during lunch breaks at work. A separate cluster of younger respondents, primarily students, more often combines car trips with public transport. Their purchases tend to be lighter, and shopping trips are shifted toward the afternoon (after 3:00 p.m.). Some studies indicate that younger people are more inclined to use environmentally friendly transport modes, partly due to their mobility and fewer established travel habits [24]. The present study partially confirms this, as the combined share of public transport and walking trips is higher in the second cluster (69% versus 61% for the first cluster). These findings provide a foundation for more targeted sustainable urban transport policies, particularly aimed at younger population groups, who are more open to changing travel behaviors. For students, it is advisable to focus on improving access to public transportation and micro-mobility infrastructure. For the employed population, incentives to reduce private car use—such as developing ride-sharing systems, enhancing walking conditions, and integrating mobility services—are particularly important.

A prospect for further research is the assessment and modeling of the impact of shopping-related travel flows on overall traffic. Considering that shopping trips using transport are most frequent between 3:00 p.m. and 6:00 p.m. (including the start of the evening peak), studying these micro-mobility flows is a highly relevant issue.

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Півторак Г.В., Пруський Є.В. **Використання кластерного аналізу для вивчення характеристик мікровантажних потоків покупців**

У статті представлено результати дослідження, спрямованого на виявлення соціально-демографічних і поведінкових чинників, що впливають на вибір способу пересування населення під час здійснення покупок. Зважаючи на зростання обсягів поїздок, пов'язаних із закупівлею товарів, і на посилення уваги до екологічних аспектів міської мобільності, у роботі розглянуто феномен мікровантажних потоків покупців як частину ширшої системи міських вантажних перевезень.

Дослідження базується на результатах онлайн-опитування 479 респондентів. На основі методу ієрархічної кластеризації визначено два основні кластери покупців. Перший кластер сформували представники середнього віку, переважно жінки, які поєднують активну зайнятість із виконанням покупок середньої ваги (2–5 кг), здебільшого у денний час, і віддають перевагу пересуванню

приватним автомобілем або пішки. Другий кластер охоплює переважно студентську молодь, яка здійснює невеликі покупки (до 2 кг), частіше після 15:00, комбінуючи громадський транспорт і піші переміщення.

Отримані результати підтверджують наявність статистично значущих відмінностей між групами за віком, статтю, видом діяльності, часом виконання та вагою покупки. Виявлено чітку залежність між вагою покупки та вибором транспортного засобу: зі зростанням ваги суттєво підвищується ймовірність використання приватного автомобіля. Аналогічно, часові характеристики впливають на модальний вибір – у ранкові години переважають піші переміщення, тоді як у пообідній період зростає частка автомобільних поїздок та поїздок громадським транспортом.

Практичне значення роботи полягає у формуванні наукового підґрунтя для розроблення цільових заходів сталого транспортного планування, зорієнтованих на конкретні групи користувачів. Для молоді доцільно зосередитися на покращенні доступності громадського транспорту та розвитку інфраструктури мікромобільності, тоді як для працюючого населення ефективними можуть бути стимули до скорочення використання приватного автомобіля.

Перспективи подальших досліджень пов’язані з моделюванням впливу покупецьких мікровантажних потоків на загальні транспортні потоки міста. Такий аналіз є важливим для управління піковими навантаженнями транспортної системи та розроблення політик екологічно сталого розвитку міських перевезень.

Ключові слова: переміщення з метою покупки, кластерний аналіз, соціально-демографічні показники, вибір виду переміщення, мікровантажні потоки

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