Annales Universitatis Paedagogicae Cracoviensis 433

Studia de Cultura 17(4) ▪ 2025
ISSN 2083–7275 (druk), ISSN 2391-4432 (online)
DOI 10.24917/20837275.17.4.8

Tomáš Koprda
Constantine the Philosopher University
ORCID: 0000-0003-1776-5491

Milan Džupina
Constantine the Philosopher University
ORCID: 0000-0003-0230-6583

Györgyi Janková
Constantine the Philosopher University
ORCID: 0000-0003-1354-7147

User Perceptions of Social Media Among Generation Z Through the UTAUT2 Model

Introduction

In recent decades, the professional and scientific community has recorded significant changes in communication, social interactions, learning, access to information, and consumer decision-making. Social media play a significant role in this context, and especially so in relation to younger generations of consumers – specifically Generation Z – which is strongly attached to digital identity. The representatives of this generation are characterized by the fact that they grew up in an environment in which the Internet, smartphones, and instant access to information were a natural part of everyday life and their consumer habits were formed significantly differently from previous generations.

Professional literature provides various terminological definitions and age distributions of the individual generations. This inconsistency stems from the inconsistency of cultural and historical aspects in some countries. In our work, we use the division that places Generation Z in the 1995-2010 framework. Our approach is based on the cultural and historical aspects of our country, taking into account the pace of modernization of information technologies.

Although the Internet creates a new world for children and young people in which they can use imagination, playfulness, and satisfy their social and other needs, it is important to be aware of the misleading and inappropriate Internet content (erotic, aggressive, racist, etc.). The negative impact of the intense contact with the media affects the value system of young people, creating pseudo-values, which usually leads to conflict in families and at school. Equally important are the dangers of the Internet that affect young people, which include online dating, grooming, human trafficking, cyberbullying, and cybertalking. The above dangers not only endanger the lives of young people, but also lead to the development of various non-substance addictions (pathological gambling, shopping, addiction to sects and cults, etc.).

For this reason, there is a significant need to examine the factors that may influence consumer, information, and media literacy through the adoption and use of digital technologies among different age and social groups. In this context, the UTAUT2 model (Venkatesh et al., 2012) appears to be a suitable methodological framework for mapping out the relationships between motivational and behavioral variables that influence the adoption of technology. This model expands the original model to include new dimensions such as hedonic motivation, habit, and value.

Literature Review

Digital Literacy and Technology Adoption

Generation Z, which emerged in the mid-1990s and early 2010s, is a generation inherently familiar with the digital environment because it grew up in a tech-driven world (Dolot, 2018; Aithal, 2024). This very connection with technology has shaped their consumer habits and digital skills, with deep immersion in the digital realm, which has an effect on how they engage with platforms and make decisions (Bassiouni & Hackley, 2014). Research has shown that their digital literacy is exceptional and plays a pivotal role in shaping their online purchasing behaviors (Kahawandala et al., 2020; Ngah et al., 2021). This advanced digital fluency allows them to navigate the digital platforms with ease, making them particularly responsive to evolving online shopping trends. Gen Z's strong inclination toward digital tools, especially mobile technologies, further highlights their comfort with the digital world (Anshari et al., 2016; Priporas, 2017). Their dependence on the smartphones for shopping underscores a seamless integration of mobile technology into their daily lives, making the mobile shopping experience central to their consumer behavior (Zhulal et al., 2024; Lapidus et al., 2024). This dependence on smartphones aligns with a growing reliance on digital interfaces, which they interact with naturally, reflecting a generation that has never known a world without instant access to information and services. Moreover, their apt use of e-wallets, which has become central to their payment habits, reflects a clear trend toward digital-first transactions (Natswa & Subagyo, 2024).

From our perspective, Generation Z's digital literacy goes beyond just purchasing products; it highlights a broader shift in how they approach the world around them. Their comfort with technology makes them more inclined to trust digital services and engage in behaviors that previous generations might have found risky, such as making purchases through mobile apps or using e-wallets. As businesses continue to evolve in response to this generation, understanding their digital fluency becomes essential. The expectation is not just for user-friendly experiences but for highly personalized, secure, and intuitive digital interactions. This generation's consumer behavior emphasizes the importance of continuously innovating within the digital landscape to meet their expectations.

Online Shopping Behavior and Purchase Decisions

Gen Z's online shopping habits are influenced by both hedonic and utilitarian factors, creating a complex blend of pleasure and practicality in their purchasing decisions (Utomo et al., 2023; Agrawal, 2022). The pleasure and enjoyment they take in browsing and making online purchases significantly shape their buying behavior, highlighting their desire for an engaging and satisfying shopping experience (Ang, 2024). However, practical considerations, such as efficiency and convenience, are also key drivers, particularly in the context of the COVID-19 pandemic, which accelerated their shift toward e-commerce (Ang, 2024; Zhulal et al., 2024).

This dual influence of enjoyment and practicality reflects the ways in which Gen Z approaches online shopping, balancing the emotional satisfaction of a seamless digital experience with the rational need for timesaving and ease. The pandemic amplified the importance of convenience, as restrictions and lockdowns pushed them to rely more heavily on online platforms for their purchases. It is not just about the thrill of shopping anymore; it is about speed, ease of access and reliability. As a result, businesses targeting this generation must offer both an enjoyable and personalized experience and the efficiency that Gen Z increasingly demands in a post-pandemic world. This dynamic is likely to continue shaping their expectations, with a growing focus on delivering quick, intuitive, and engaging e-commerce environments.

The Power of Social Media in Shaping Gen Z's Purchasing Behavior

Social media play a vital role in shaping the Gen Z's purchasing behavior, influencing nearly every aspect of their consumer journey (Erwin et al., 2023). Platforms like Instagram and TikTok have become pivotal to their product discovery and decision-making processes, serving as key avenues through which Gen Z engages with brands and products (Haenlein et al., 2020). The ability to see products in real-life contexts and hear firsthand experiences from peers makes these platforms a powerful source of influence. User-generated content (UGC) and endorsements from micro-celebrities are particularly effective at guiding Gen Z's purchasing decisions. This generation relies heavily on peer recommendations and social proof, trusting the experiences of people they can relate to over traditional advertising (Bhuwaneshwari, Hemasuruthi, 2023; Shetu, 2023). This trend reflects their desire for authenticity and relatability in the content they consume. Moreover, influencers — especially those perceived as authentic and trustworthy — hold significant sway over Gen Z's preferences, making their opinions a driving force in purchasing behaviors (Misron et al., 2024; Bhuwaneshwari, Hemasuruthi, 2023). For Gen Z, social media are not just a space for entertainment or communication; they play a crucial role on their entire consumer journey, shaping their decisions from start to finish (Gerasimova, 2024; Siregar et al., 2023). Platforms like YouTube and TikTok serve as essential tools for researching and assessing products, allowing Gen Z to review information, watch tutorials or hear the reviews before making a purchase (Erenia, Faustino, Morales, 2024). This ability to gather insights directly from fellow consumers or creators provides them with a sense of control over their buying process, reinforcing the importance of social media as a research tool. Beyond individual choices, the impact of social media extends to broader cultural and environmental trends, influencing the way Gen Z interacts with the world around (Bolton et al., 2013). For example, social media campaigns and influencer advocacy play an important role in raising environmental awareness in Gen Z who are increasingly inclined toward sustainable consumption practices (Anderson, 2021; Duong, Tran, 2024). This demonstrates the dual function of social media — they are both a marketing tool and a catalyst for social change, shaping the consumer attitudes toward sustainability and driving green purchase intentions (Tass, 2025). Social media, therefore, have the power to influence the individual buying decisions and also foster a shift in societal values, pushing for more conscious consumerism (Mahoney, Tang, 2024).

Materials & Methods

This research study aims to clarify the factors that determine the people's intentions to use social media to share content about their experiences. Given that social media are actually technological applications, our research study made use of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) as a theoretical framework. The UTAUT2 theory was defined by Venkatesh, Thong, and Xu (2012). This theoretical model includes Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivations, Habit, and Price Value in technology use as explanatory variables.

The main research objective was to identify the key predictors influencing the behavioral intention and actual use of social media by Generation Z based on the UTAUT2 (Unified Theory of Acceptance and Use of Technology) model. Our partial research goal was to determine the difference between the behavioral intention to use social media (Behavioral Intention) and the actual use (Use Behavior) of social media by Generation Z.

The factors of the UTAUT2 model were defined by Venkatesh et al. (2012, p. 159) as follows. Performance Expectancy is the extent to which an individual believes that the use of technology will help them achieve better results at work or study. Effort Expectancy is the extent to which an individual perceives the use of technology as easy and effortless. Social Influence is the extent to which an individual perceives that people they care about (e.g., colleagues, superiors, friends) think they should use technology. Facilitating Conditions are the extent to which an individual believes they have sufficient support (technical, organizational, knowledge) available to them to use the technology effectively, and Hedonic Motivation is the extent to which an individual perceives the use of technology as fun and enjoyable. Price Value is defined as the cognitive trade-off between the perceived benefits of an application and the monetary cost of its use. In other words, it is about how the consumers perceive whether the price they pay for a technology or service is adequate to its benefits. Habit is the extent to which people tend to perform a particular behavior automatically as a result of learning. It is a repetitive behavior that becomes routine and requires minimal conscious effort. For research purposes, we did not use the Price Value construct because social media are used free of charge. The ownership of technology (smartphone, computer) can be considered as the only financial expense.

Based on the theoretical UTAUT2 model, we set the following research hypotheses:

- H1: Based on the UTAUT2 model, we assume that Performance Effort has a significant impact on Behavioral Intention to use social media by Generation Z.

- H2: Based on the UTAUT2 model, we assume that Effort Expectancy has a significant impact on Behavioral Intention to use social media by Generation Z.
- H3: Based on the UTAUT2 model, we assume that Social Influence has a significant impact on Behavioral Intention to use social media by Generation Z.
- H4: Based on the UTAUT2 model, we assume that Facilitating Conditions have a significant impact on Behavioral Intention to use social media by Generation Z.
- H5: Based on the UTAUT2 model, we assume that Hedonic Motivation has a significant impact on Behavioral Intention to use social media by Generation Z.
- H6: Based on the UTAUT2 model, we assume that Habit has a significant impact on Behavioral Intention to use social media by Generation Z.
- H7: Based on the UTAUT2 model, we assume that Behavioral Intention has a significant impact on Use Behavior of social media by Generation Z.
- H8: We assume that Social Influence has a significant impact on Use Behavior of social media by Generation Z.
- H9: We assume that Hedonic Motivation has a significant impact on Use Behavior of social media by Generation Z.
- H10: Based on the UTAUT2 model, we assume that Habit has a significant impact on Use Behavior of social media by Generation Z.
- H11: We assume that Facilitating Conditions have a significant impact on Use Behavior of social media by Generation Z.

We used structural equation modeling (SEM) with partial least squares (PLS-SEM) to evaluate the UTAUT2 model. We performed the calculations in SmartPLS 4.1.1.1 and followed the publications by Hair (2021) and Latan and Noonan (2017).

The total number of respondents in our research was N = 155. The respondents were students from several universities in Slovakia aged 19 to 26. They were from Generation Z and studied Media and Communication. We determined the number of respondents using the inverse square root method. Assuming a significance level of 5% and a minimum path coefficient of 0.2, the minimum sample size is calculated as $n_{min} > (2.486 / 0.2)^2 = 154.505$, which can be rounded up to 155. Our research set corresponds to this minimum sample.

Results

Using SmartPLS software, we first examined the Measurement Model to assess the reliability and validity of data before testing the Structural Model.

Measurement Model

The Measurement Model, also called External Model in the context of PLS-SEM (Partial Least Squares Structural Equation Modeling), describes the relationships between latent variables (constructs) and their measurements (indicators). In other words, it specifies how latent variables are measured using their indicators. The goal of the Measurement Model is to determine how well the indicators measure the relevant construct.

The UTAUT2 model is a reflective measurement model (Venkatesh et al., 2012). This model assumes that indicators form a construct. First, we assessed the Internal Consistency Reliability, Convergent Validity, and Discrimination Validity of the Measurement Model.

Internal Consistency Reliability

We used the following metrics to assess Internal Consistency Reliability: composite reliability rho_A and rho_C, and Cronbach's alpha. Internal Consistency Reliability deals with the extent to which indicators measuring the same construct are related to each other.

Composite reliability (rho_A) is considered an important estimate of the reliability of construct scores in PLS-SEM. Currently, this is the only consistent reliability measure for the construct scores in PLS. A minimum value of 0.70 is recommended for rho_A. Values between 0.70 and 0.90 are considered satisfactory to good, while the values between 0.60 and 0.70 are acceptable in exploratory research. Values above 0.95 are problematic because they indicate that the indicators are redundant, reducing the validity of the construct (Hair et al., 2021; Dijkstra and Henseler, 2015). The same values are also used for the rho_C metric.

Cronbach's alpha is another measure of Internal Consistency Reliability that assumes equal loadings of all indicators in the population (tau-equivalence). A violation of this assumption may lead to lower reliability values compared to rho_A. Nevertheless, even in the absence of tau-equivalence, Cronbach's alpha has been shown to be an acceptable lower bound approximation of true internal consistency reliability (Bonett and Wright, 2015). The threshold values that apply to Cronbach's alpha also apply to composite reliability rho_A and rho_C.

The results of assessment of Internal Consistency Reliability of the Measurement Model are presented in Table 1.

Table 1: Internal consistency of reliability of the Measurement Model

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.881	0.917	0.943	0.893
EE	0.918	0.942	0.938	0.790
FC	0.729	0.762	0.843	0.642
HM	0.882	0.896	0.927	0.810
HT	0.796	0.852	0.878	0.709
PE	0.900	0.900	0.931	0.771
SI	0.870	0.879	0.920	0.794
USE	0.698	0.701	0.746	0.501

Convergent Validity

Several methods are used to assess Convergent Validity in reflective measurement models in PLS-SEM, with Average Variance Extracted (AVE) being the dominant measure (Fornell and Larcker, 1981). Convergent Validity refers to the extent to which indicators (measured variables) that should theoretically be related are actually related. In other words, it verifies whether indicators of one construct actually measure the same underlying construct.

In general, an AVE value of 0.5 or higher is considered acceptable. This means that more than 50% of the variance in the indicators should be explained by the given construct (Latan and Noonan, 2017).

The results of assessment of Convergent Validity of the Measurement Model are presented in Table 1.

Discrimination Validity

Discrimination Validity refers to the extent to which a construct differs from other constructs in the model. In other words, we verify whether constructs that should be theoretically different are actually different statistically. Two criteria are used to assess Discrimination Validity in the reflective PLS-SEM measurement models (Voorhees et al., 2016): the Fornell-Larcker criterion (Fornell and Larcker, 1981) and the Heterotrait-Monotrait (HTMT) correlation ratio (Henseler, 2015).

The Fornell-Larcker criterion states that the average variance extracted (AVE) of a construct should be higher than its squared correlations with all other constructs in the model. If this condition is met for all constructs, it is assumed that adequate discriminant validity (Fornell and Larcker, 1981) exists. Although the criterion was often used in the past, recent research suggests (Henseler, Ringle, and Sarstedt, 2015) that the Fornell-Larcker criterion is not suitable for reliably detecting the problems with discriminant validity. Therefore, we decided to not assess Discrimination Validity according to this criterion.

The Heterotrait-Monotrait (HTMT) correlation ratio is more accurate for estimating the correlation between the factors. To distinguish between two factors, the HTMT should be statistically significantly less than 1. Some sources recommend a stricter limit, for example HTMT < 0.90 (Hair et al., 2021; Henseler, Ringle, and Sarstedt, 2015). The HTMT is considered a more informative criterion of Discrimination Validity compared to the Fornell-Larcker criterion. The HTMT value should be less than 0.90 for the proposed HTMT cutoff values for constructs that are conceptually very similar. For constructs that are more conceptually distinct, a more conservative cutoff value of < 0.85 is recommended. A value above 0.90 would indicate an absence of Discrimination Validity.

The results of assessment of Discrimination Validity of the Measurement Model are presented in Table 2.

Table 2: Discrimination Validity of the Measurement Model (HTMT)

	BI	EE	FC	HM	HT	PE	SI	USE
BI								
EE	0.234							
FC	0.436	0.790						
HM	0.486	0.442	0.857					
HT	0.472	0.435	0.680	0.669				
PE	0.778	0.241	0.372	0.404	0.423			
SI	0.478	0.614	0.861	0.646	0.477	0.405		
USE	0.627	0.536	0.785	0.739	0.880	0.448	0.760	

To verify Discrimination Validity, we also performed a cross-loading assessment. Cross-loadings should be assessed to ensure that no indicator is incorrectly assigned to the wrong construct. Each indicator should have the highest loading on its assigned construct compared to its loadings on other constructs.

The results of assessment of Discrimination Validity of the Measurement Model with the help of cross-loadings are presented in Table 3.

Table 3: Cross-loadings

	BI	EE	FC	HM	HT	PE	SI	USE
BI1	**0.958**	0.279	0.442	0.472	0.419	0.686	0.440	0.505
BI2	**0.932**	0.183	0.267	0.350	0.315	0.625	0.351	0.293
EE1	0.149	**0.871**	0.534	0.312	0.373	0.127	0.490	0.343
EE2	0.139	**0.859**	0.505	0.306	0.249	0.194	0.404	0.276
EE3	0.327	**0.926**	0.644	0.469	0.460	0.297	0.590	0.517
EE4	0.159	**0.899**	0.554	0.337	0.362	0.167	0.517	0.372
FC2	0.188	0.731	**0.781**	0.428	0.475	0.210	0.530	0.421
FC3	0.443	0.407	**0.838**	0.715	0.431	0.376	0.561	0.509
FC4	0.237	0.477	**0.783**	0.516	0.417	0.144	0.573	0.386
HM1	0.467	0.390	0.650	**0.929**	0.607	0.366	0.556	0.524
HM2	0.403	0.394	0.673	**0.922**	0.467	0.317	0.537	0.502
HM3	0.307	0.365	0.604	**0.846**	0.505	0.292	0.437	0.464
HT1	0.396	0.511	0.654	0.661	**0.892**	0.338	0.517	0.558
HT2	0.331	0.072	0.223	0.279	**0.706**	0.282	0.131	0.276
HT3	0.287	0.403	0.430	0.481	**0.913**	0.287	0.379	0.651
PE1	0.633	0.188	0.297	0.347	0.288	**0.869**	0.284	0.230
PE2	0.607	0.309	0.355	0.299	0.386	**0.884**	0.357	0.252
PE3	0.593	0.178	0.238	0.283	0.254	**0.924**	0.301	0.247
PE4	0.610	0.180	0.248	0.342	0.319	**0.833**	0.315	0.282
SI1	0.385	0.614	0.637	0.521	0.497	0.327	**0.900**	0.563
SI2	0.367	0.582	0.652	0.523	0.437	0.317	**0.923**	0.511
SI3	0.380	0.335	0.547	0.478	0.207	0.313	**0.849**	0.415
USE1	0.346	0.500	0.608	0.582	0.570	0.180	0.577	**0.859**
USE2	0.359	0.149	0.143	0.177	0.441	0.340	0.169	**0.650**
USE3	0.227	0.221	0.310	0.313	0.244	0.135	0.356	**0.587**

Indicator Reliability

Assessing Indicator Reliability is an important step in evaluating the reflective measurement models, including the UTAUT2 model. **Indicator Reliability** is assessed to determine how much of the variance in each indicator is explained by the construct it is intended to measure. **Indicator loading** is used to assess the reliability of an indicator. Indicator loading is the bivariate correlation between an indicator and a construct.

It is recommended that indicator loadings be higher than 0.708. (Hair et al., 2021). This criterion is based on the fact that the construct should explain more than 50 percent of the variance of the indicator ($0.708^2 \approx 0.501$). Indicator readings above 0.708 therefore indicate an acceptable level of indicator reliability.

We often encounter weaker indicator loadings (< 0.708) in the social sciences especially when using new scales (Hulland, 1999). In such cases, researchers should not automatically get rid of indicators, but rather carefully consider how their removal affects other measures of reliability and validity. In general, indicators with loadings between .40 and .708 should be considered for removal only if removing the indicator results in an increase in Internal Consistency Reliability or Convergent Validity. However, indicators with very low loadings (below 0.40) should always be eliminated from the Measurement Model (Hair, Hult, Ringle, & Sarstedt, 2022).

The results of the Indicator Reliability assessment are presented in Table 4.

Table 4: Indicator Reliability – Indicator loadings

	BI	EE	FC	HM	HT	PE	SI	USE
BI2	0.958							
BI3	0.932							
EE1		0.871						
EE2		0.859						
EE3		0.926						
EE4		0.899						
FC2			0.781					
FC3			0.838					
FC4			0.783					
HM1				0.929				
HM2				0.922				
HM3				0.846				
HT1					0.892			
HT2					0.706			
HT3					0.913			
PE1						0.869		
PE2						0.884		
PE3						0.924		
PE4						0.833		
SI1							0.900	
SI2							0.923	
SI3							0.849	
USE1								0.859
USE2								0.650
USE3								0.587

Structural Model

In the context of structural equation modeling (SEM) and specifically in PLS-SEM, a Structural Model represents the part of a complex model that specifies the relationships between constructs (latent variables). Unlike the Measurement Model, which defines the relationships between latent constructs and their measured indicators, a Structural Model focuses on causal or predictive relationships between the constructs themselves (Hair et al., 2021). A Structural Model shows how one or more constructs are hypothesized to influence other constructs. These relationships are represented by directional arrows in the model diagrams where an arrow pointing from construct A to construct B indicates that A is hypothesized to be the predictor or causal variable and B is the dependent or affected variable.

There are two main types of latent variables in structural equation models (SEM): exogenous and endogenous latent variables. Exogenous latent variables are constructs that only explain other constructs in a given model. In other words, they are independent variables in a structural model. Endogenous latent variables are constructs that are explained by other constructs in a given model. They can serve as dependent variables.

When evaluating the structural model, we first assessed collinearity, followed by the examination of significance and relevance of the path coefficients, and lastly, we evaluated the coefficient of determination (R^2).

Collinearity

Before evaluating the relationships between constructs, it is important to assess potential issues with multicollinearity among the predictive constructs. Assessing collinearity in a structural model refers to detecting high correlation between the predictor constructs (latent variables or composites) that influence an endogenous construct. High collinearity can make it difficult to interpret the individual contribution of each predictor to explaining variance in the dependent variable (Latan and Noonan, 2017). We assessed collinearity using the Variance Inflation Factor (VIF) values.

The strictest threshold for VIF values is less than 5. It is often recommended to ensure that multicollinearity does not significantly affect the regression results. A VIF value of less than 5 indicates that the variance of the regression coefficients is slightly higher, but the impact on the reliability of the estimates is minimal (O'Brien, 2007).

The results of the Collinearity assessment are presented in Table 5.

Table 5: Variance Inflation Factor (VIF)

	VIF
BI -> USE	1.348
EE -> BI	1.888
FC -> BI	3.255
FC -> USE	2.771
HM -> BI	2.424
HM -> USE	2.411
HT -> BI	1.690
HT -> USE	1.652
PE -> BI	1.232
SI -> BI	2.151
SI -> USE	2.039

Significance and Relevance of relationships between constructs (Path Coefficients)

Path Coefficients in the Structural Model are standardized regression coefficients that indicate the direction and strength of the linear relationship between two latent variables (constructs) or composites in a structural equation model (Latan and Noonan, 2017, p. 103). In the context of PLS-SEM, these coefficients quantify the direct effect of one construct on another within a specified structural model.

The values of Path Coefficients range from -1 (strong negative relationships) to +1 (strong positive relationships) and determine the direction of the relationship. A positive Path Coefficient means that as the value of the predictor construct increases, the value of the dependent construct also increases, assuming the other variables in the model are constant. A negative Path Coefficient means that as the value of the predictor construct increases, the value of the dependent construct decreases, assuming the other variables are constant.

The strength of the relationship is determined by the absolute value of the coefficient, which indicates the strength of the effect. A coefficient closer to +1 or -1 represents a stronger relationship and a coefficient closer to 0 indicates a weaker relationship. Since Path Coefficients are usually standardized in PLS-SEM (variables have a mean of 0 and a standard deviation of 1), they allow for a direct comparison of the strength of the effects of different predictor constructs on the same dependent variable. Bootstrapping (Hair et al., 2021) is commonly used in PLS-SEM to assess whether the estimated path coefficient is statistically significant (i.e. whether it is highly likely to differ from zero in the population).

Bootstrapping is a nonparametric method used to estimate the standard errors of Path Coefficients and to determine their p-values and confidence intervals. If the confidence interval does not contain a zero and the p-value is lower than the chosen significance level (e.g. 0.05) or the t-value is greater than 1.96, then the Path Coefficient is statistically significant. We validated our hypotheses with the bootstrapping method.

The results of Path Coefficients are presented in Table 6.

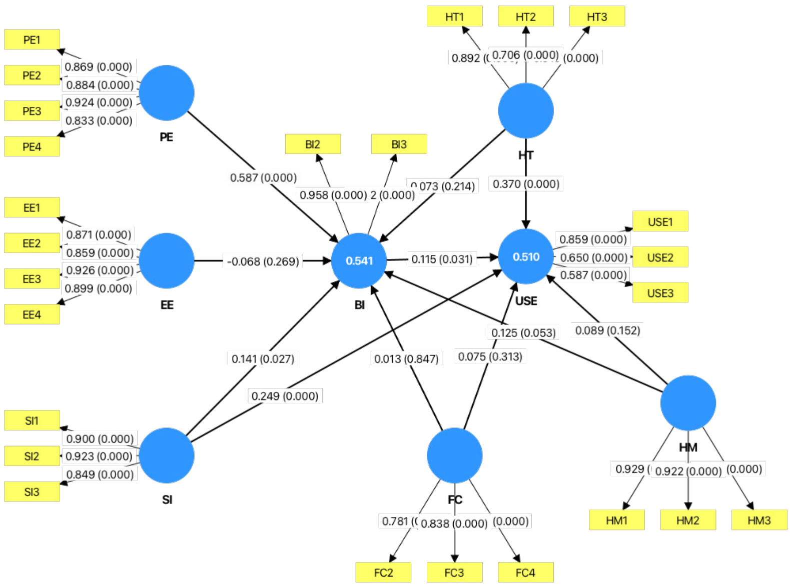
Table 6: Path Coefficients in the Structural Model

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P-values
PE -> BI	0.587	0.585	0.041	14.255	0.000
SI -> BI	0.141	0.138	0.064	2.210	0.027
HM -> BI	0.125	0.125	0.065	1.932	0.053
HT -> BI	0.073	0.075	0.058	1.242	0.214
FC -> BI	0.013	0.013	0.065	0.193	0.847
EE -> BI	-0.068	-0.060	0.061	1.104	0.269
HT -> USE	0.370	0.371	0.072	5.109	0.000
SI -> USE	0.249	0.248	0.071	3.518	0.000
BI -> USE	0.115	0.111	0.054	2.155	0.031
HM -> USE	0.089	0.088	0.062	1.434	0.152
FC -> USE	0.075	0.083	0.075	1.008	0.313

The coefficient of determination, denoted as R^2, is used in the context of evaluating a structural model in PLS-SEM to assess the amount of variance of an endogenous (dependent) variable (construct) that is explained by its predictor variables in the model. In other words, R^2 indicates how well the predictor constructs together explain the variability in the dependent construct.

The R^2 value ranges from 0 to 1 where: if $R^2 = 0$, the model explains no part of the variance in the endogenous variable, and if $R^2 = 1$, the model perfectly explains all the variance in the endogenous variable. Higher R^2 values indicate better explanatory power of the model for a given endogenous variable. Conversely, lower R^2 values mean that the model explains a smaller portion of the variance, and thus the other unincluded factors may significantly influence the dependent variable.

Graph 1: Model in SmartPLS



Evaluation of the Coefficient of Determination (R^2)

In general, however, there are no strict universal border values for "good" R^2. The adequacy of R^2 depends on the research context, complexity of the model and the examined discipline. In some areas of social sciences, an R^2 of around 0.20 may be considered acceptable, while in others significantly higher values are expected. Latan and Ghozali (2015) suggest that R^2 values between 0.425 and 0.507 can be considered "approaching material". Hair, Ringle and Sarstedt (2011) suggest that the following guideline values are often used in social sciences for assessing R^2: 0.75 is considered to have substantial explanatory power, 0.50 moderate explanatory power, and 0.25 weak explanatory power.

The resulting coefficient of determination R^2 is presented in Table 7.

Table 7: Coefficient of determination (R^2)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P-values
BI	0.541	0.548	0.044	12.287	0.000
USE	0.510	0.524	0.051	9.951	0.000

Discussion

The results of the analysis of hypotheses according to the UTAUT2 model show that Performance Effort significantly positively influences Behavioral Intention (H1: $\beta = 0.587$, SE = 0.041, t = 14.255, $p < 0.001$), indicating a strong relationship.

However, Effort Expectancy does not show a statistically significant relationship with Behavioral Intention (H2: $\beta = -0.068$, SE = 0.061, t = 1.104, p = 0.269), indicating that the effort expended on using social media does not play a significant role in this case.

Social Influence has a positive and statistically significant – although weak – effect on Behavioral Intention (H3: $\beta = 0.141$, SE = 0.064, t = 2.210, p = 0.027) to use social media.

On the other hand, the effects of Facilitating Conditions are very weak and statistically insignificant (H4: $\beta = 0.013$, SE = 0.065, t = 0.193, p = 0.847).

Hedonic Motivation has a slightly positive relationship with Behavioral Intention, but the relationship did not reach statistical significance (H5: $\beta = 0.125$, SE = 0.065, t = 1.932, p = 0.053).

Habit also does not show a significant effect on Behavioral Intention (H6: $\beta = 0.073$, SE = 0.058, t = 1.242, p = 0.214).

Behavioral Intention has a weak but statistically significant positive effect on Use Behavior (H7: $\beta = 0.115$, SE = 0.054, t = 2.155, p = 0.031).

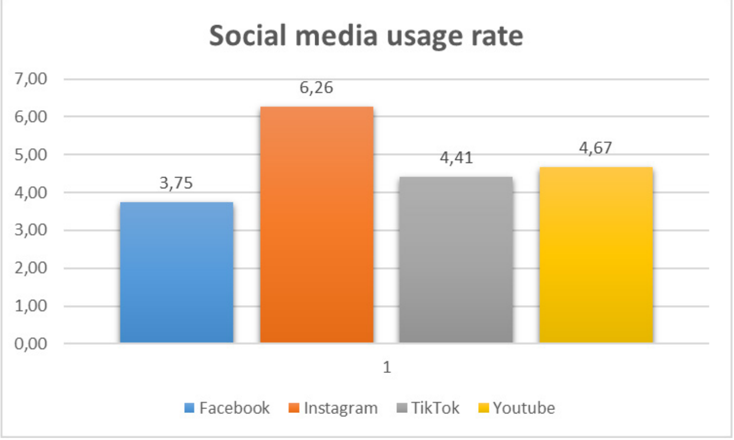
Social Influence (H8: $\beta = 0.249$, SE = 0.071, t = 3.518, $p < 0.001$) and Habit (H10: $\beta = 0.370$, SE = 0.072, t = 5.109, $p < 0.001$) also significantly positively influence the Use Behavior, while the influence of Habit can be described as moderately strong.

On the contrary, Hedonic motivation has a weak and statistically insignificant effect on the actual Use Behavior (H9: $\beta = 0.089$, SE = 0.062, t = 1.434, p = 0.152), as do Facilitating Conditions (H11: $\beta = 0.075$, SE = 0.075, t = 1.008, p = 0.313).

In the research, we examined the preference and frequency of use of individual social media. The respondents expressed their opinions on a scale from 1 to 7 (never - always). The results indicated a gradual decline of Facebook in this Generation (Mean: 3.75). TikTok and YouTube have averages values of 4.41 and 4.67. Instagram is close to the "always" answer (Mean: 6.26). The results are presented in Table 8 and graphically in Graph 2.

Table 8: Social media usage rate

		Facebook	Instagram	TikTok	YouTube
N	Valid	155	155	155	155
	Missing	0	0	0	0
Mean		3.75	6.26	4.41	4.67
Std. Error of Mean		.16	.11	.21	.14
Median		3.00	7.00	5.00	5.00
Std. Deviation		2.02	1.32	2.55	1.77
Minimum		1.00	1.00	1.00	1.00
Maximum		7.00	7.00	7.00	7.00



Graph 2: Social media usage rate – means

Results from other studies (Petropoulos Petalas et al., 2021) suggest that (Gen Z) teens used social media platforms (mean 3.27) more than young adults (mean 3.87). It was also found that younger users have more followers on platforms like Instagram and Snapchat, while young adults have more followers on Facebook. This suggests that Generation Z is engaging more actively and diversely on social media compared to the previous generations. The research used a four-wave panel survey on a representative national sample of 3,669 participants divided into two age groups: adolescents (aged 12-17) and young adults (aged 18-25). Further research (Pérez-Escoda et al., 2021) suggests that Generation Z prefers platforms such as Spotify, TikTok, Snapchat, and Twitch over Facebook and Twitter, which are more popular among millennials. Plus, they are heavy consumers of social media and often use them for real-time information, and they do not consider traditional media to be authoritative. Unlike previous generations, Gen Z is actively involved in content creation and production and perceives the established news sources and social media influencers as equally trustworthy. This shift reflects their unique relationship to technology and information consumption. This trend was also confirmed in our results.

Overall, we can conclude that Performance Effort, Social Influence, and Habit play a significant role in explaining the intention to use and the actual use of social media in the investigated UTAUT2 model, while Effort Expectancy, Hedonic Motivation, and Facilitating Conditions are less relevant or statistically insignificant in this context.

Behavioral Intention was examined in the UTAUT2 model and the results show that the predictors used in the model explain 54.1% of the variance in Behavioral Intention, which is a statistically significant result ($R^2 = 0.541$, $SE = 0.041$, $t = 12.287$, $p < 0.001$). This result suggests that the UTAUT2 model can significantly predict the individuals' Behavioral Intention to use social media.

Regarding Use Behavior, the UTAUT2 model explains 51.0% of the variance in technology use ($R^2 = 0.510$, $SE = 0.051$, $t = 9.951$, $p < 0.001$), which also represents a statistically significant result. This means that the variables in the model sufficiently explain the actual social media use by Generation Z.

Overall, we can conclude that both dependent variables ("Behavioral Intention" and "Use Behavior") are well explained by the variables used in the UTAUT2 model, while the achieved values of the coefficients of determination (R^2) indicate a very good explanatory power of the model.

Conclusion

The research study aimed to identify the key factors that influence the intention and actual use of social media by Generation Z in Slovakia. The authors of this study used the theoretical framework of the UTAUT2 model, which allows for the analysis of the adoption of digital technologies with the help of various behavioral and motivational variables. The research sample consisted of 155 respondents aged 19 to 26, all students of Media and Communication at Slovak universities. Using the structural equation modeling method (PLS-SEM), the hypotheses about the influence of individual factors on Behavioral Intention and Use Behavior of social media were tested. The results showed that the most significant predictor of the intention to use social media was Performance Expectancy, which had a strong positive and statistically significant effect. Even Social Influence had a statistically significant, albeit weaker, effect. Conversely, factors such as Effort Expectancy, Hedonic Motivation, Habit, and Facilitating Conditions were found to be statistically insignificant in relation to Behavioral Intention. When analyzing actual social media Use Behavior, it was found that Habit has the most significant influence, followed by Social Influence and Behavioral Intent. However, Hedonic Motivation and Facilitating Conditions again did not show a statistically significant effect. The UTAUT2 model was able to explain 54.1% of the variability in Behavioral Intention and 51% in Use Behavior, which indicates its high predictive ability in the context of the phenomenon under review. The research also showed that Instagram dominates among social media platforms and is used most frequently. TikTok and YouTube were medium popular, while Facebook is on a downward trajectory among this generation. The results point to a shift in communication and media preferences in Generation Z, which favors fast, visual, and interactive platforms.

Overall, the study confirms that Performance Expectancy, Social Influence, and Habit are key variables in the adoption and use of social media by the young generation. On the contrary, aspects such as effort, fun, or technical conditions play a lesser or no significant role. The results are a valuable contribution for experts in the fields of Media Communication, Marketing, and Education, as they offer a deeper insight into the digital behavior of a generation that will increasingly determine the future development of society.

The publication was supported by the KEGA project no. 023UKF-4/2024 Innovative education and development of consumer, information, and media (SIM) literacy in young adults in the European area.

Bibliography

Agrawal Durgesh Kumar. 2022. "Determining behavioural differences of Y and Z generational cohorts in online shopping". International Journal of Retail & Distribution Management no. 50(7). 880–895. https://doi.org/10.1108/IJRDM-12-2020-0527.

Aithal Perdoor Sreeramana. 2024. "Global Internet-based Growing (GIG) Economy – Challenges and Opportunities for Tech Generations Z and Alpha". Emerging Trends in Management Science no. 12.

Anderson Alison. 2021. "Sustainability in environmental communication research: emerging trends and future challenges". In: The Sustainability Communication Reader: A Reflective Compendium. 31–50. https://doi.org/10.4324/9781003139180-4.

Ang Yvonne. 2024. "Understanding Gen Z's online purchase behavior through their hedonic and utilitarian motivation". Information Management and Business Review no. 16(3S). 461–474. https://doi.org/10.22610/imbr.v16i3S(I)a.4217.

Anshari Muhammad, Alas Yabit, Hardaker Glenn, Jaidin Jainatul Halida, Smith Mark, Ahad Annie D. 2016. "Smartphone habit and behavior in Brunei: Personalization, gender, and generation gap". Computers in Human Behavior no. 64. 719–727. https://doi.org/10.1016/j.chb.2016.07.063.

Bassiouni Dina H., Hackley Chris. 2014. "'Generation Z' children's adaptation to digital consumer culture: A critical literature review". Journal of Customer Behaviour no. 13(2). 113–133.

Bhuwaneshwari M., Hemasuruthi S. 2023. "A Study on social media influences on Generation Z buying behaviour". International Journal of Advanced Research in Science, Communication and Technology (IJARSCT) no. 3(3). 89–95.

Bolton Ruth N., Parasuraman A. Parsu, Hoefnagels Ankie, Migchels Nanne, Kabadayi Sertan, Gruber Thorsten, Komarova Loureiro Yuliya, Solnet David. 2013. "Understanding Generation Y and their use of social media: a review and research agenda". Journal of Service Management no. 24(3). 245–267. https://doi.org/10.1108/09564231311326987.

Bonett Douglas G., Wright Thomas A. 2015. "Cronbach's alpha reliability: Interval estimation, hypothesis testing, and sample size planning". Journal of Organizational Behavior no. 36(1). 3–15. https://doi.org/10.1002/job.1960.

Dijkstra Theo K., Henseler Jörg. 2015. "Consistent partial least squares path modeling". MIS Quarterly no. 39(2). 297–316. https://doi.org/10.25300/MISQ/2015/39.2.02.

Dolot Anna. 2018. "The characteristics of Generation Z". e-mentor no. 74(2). 44–50.

Duong Hoai Lan, Tran Minh Tung. 2024. "Virtual Voices for Sustainable Values: Exploring Content Themes and Advocacy Strategies in the Sustainability Promotion of Virtual Influencers". Communication Today no. 15(1). 116–137.

Erwin, Saununu Syamsul J., Rukmana Astri Yuni. 2023. "The influence of social media influencers on generation Z consumer behavior in Indonesia". West Science Interdisciplinary Studies no. 1(10). 1028–1038. https://doi.org/10.58812/wsis.v1i10.317.

Fornell Claes, Larcker David F. 1981. "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error". Journal of Marketing Research no. 18(1). 39–50. https://doi.org/10.1177/002224378101800104.

Gerasimova Anastasia. 2024. Social Media and Generation Z: A Qualitative Inquiry into Usage Patterns and Motivations of Women of Older Gen Z.

Erenia G.R., Faustino D.M., Morales K. 2024. "Search behavior of Gen Z on YouTube and TikTok". International Journal of Science and Research Archive no. 12(1). 1023–1032. https://doi.org/10.30574/ijsra.2024.12.1.0888.

Haenlein Michael, Anadol Ertan, Farnsworth Tyler, Hugo Harry, Hunichen Jess, Welte Diana. 2020. "Navigating the new era of influencer marketing: How to be successful on Instagram, TikTok, & Co.". California Management Review no. 63(1). 5–25.

Hair Joseph F., Hult G. Tomas M., Ringle Christian M., Sarstedt Marko. 2022. A primer on partial least squares structural equation modeling (PLS-SEM). Thousand Oaks.

Hair Joseph F., Hult G. Tomas M., Ringle Christian M., Sarstedt Marko, Danks Nicholas P., Ray Soumya. 2021. Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook. Cham. https://doi.org/10.1007/978-3-030-80519-7.

Henseler Jörg. 2015. Is the whole more than the sum of its parts? On the interplay of marketing and design research. Enschede. https://ris.utwente.nl/ws/files/5119155/oratieboekje_Henseler.pdf.

Henseler Jörg, Ringle Christian M., Sarstedt Marko. 2015. "A new criterion for assessing discriminant validity in variance-based structural equation modeling". Journal of the Academy of Marketing Science no. 43(1). 115–135. https://doi.org/10.1007/s11747-014-0403-8.

Hulland John. 1999. "Use of partial least squares (PLS) in strategic management research: A review of four recent studies". Strategic Management Journal no. 20(2). 195–204. https://doi.org/10.1002/(SICI)1097-0266(199902)20:2<195::AID-SMJ13>3.0.CO;2-7.

Kahawandala Nimesh, Peter Shanika, Niwunhella Hiruni. 2020. "Profiling purchasing behavior of Generation Z". In: 2020 International Research Conference on Smart Computing and Systems Engineering (SCSE). IEEE. 155–160.

Lapidus Larisa Vladimirovna, Gostilovich Aleksandr O., Zhiburt Polina E., Karaseva M. O., Samokhvalova Ekaterina I., Kozlova Elena D. 2024. "Dynamics of development of consumer preferences and behavioral patterns of generation Z in the digital economy". Proceedings of the Southwest State University. Series: Economics. Sociology. Management no. 14(3). 73–92. https://doi.org/10.21869/2223-1552-2024-14-3-73-92.

Latan Hussein, Noonan Richard (red.). 2017. Partial Least Squares Path Modeling. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-64069-3.

Lu'ay Natswa Salsabilla. 2024. "Gen Z's Cashless Behavior: How QRIS Moderating Digital Financial Literacy and Spending Behavior Affects on E-Wallet Utilization?". KnE Social Sciences no. 9(4). 306–324. https://doi.org/10.18502/kss.v9i4.15078.

Mahoney L. Meghan, Tang Tang. 2024. Strategic social media: From marketing to social change. Hoboken.

Misron Aervina, Gabor Hairi, Rao Sobana, Ming Choo. 2024. "The impact of social media influencers on Generation Z's consumer buying behavior: A conceptual analysis". International Journal of Academic Research in Business and Social Sciences no. 14. https://doi.org/10.6007/IJARBSS/v14-i11/23248.

Ngah Rohana, Azizan Noor Azlinna, Abdul Kadir Mohd Ali Bahari, Thuraisamy Ramanathan, Mohamad Zaimah, Danila Nevi. 2021. "Exploring antecedents of online purchasing behavioral intention of Generation Z: An integrated model of four theories". Malaysian Journal of Consumer and Family Economics no. 27(1). 1–24.

O'Brien Robert M. 2007. "A caution regarding rules of thumb for variance inflation factors". Quality & Quantity no. 41(5). 673–690. https://doi.org/10.1007/s11135-006-9018-6.

Pérez-Escoda Ana, Barón-Dulce Gema, Rubio-Romero Juana. 2021. "Mapeo del consumo de medios en los jóvenes: redes sociales, 'fake news' y confianza en tiempos de pandemia". Index Comunicación no. 11(2). 187–208. https://doi.org/10.33732/IXC/11/02MAPEOD.

Petropoulos Petalas Diamantis, Konijn Elly A., Johnson Benjamin K., Veldhuis Jolanda, Bij de Vaate Nadia A. J. D., Burgers Christian, Droog Eline, Międzobrodzka Ewelina, Balint Kinga E., van de Schoot Rens. 2021. "Plurality in the measurement of social media use and mental health: An exploratory study among adolescents and young adults". Social Media + Society no. 7(3). https://doi.org/10.1177/20563051211035353.

Priporas Constantinos Vasilios, Stylos Nikolaos, Fotiadis Anestis K. 2017. "Generation Z consumers' expectations of interactions in smart retailing: A future agenda". Computers in Human Behavior no. 77. 374–381. https://doi.org/10.1016/j.chb.2017.01.058.

Putra I Komang Rajendra, Darma Gede Sri. 2020. "Process of decisions making purchase online on Instagram social media". International Journal of Business, Economics and Management no. 3(1). 165–171. https://doi.org/10.31295/ijbem.v3n1.167.

Salam Karta Negara, Pratiwi Dhita A. R. 2024. "Gen-Z marketing strategies: Understanding consumer preferences and building sustainable relationships". Golden Ratio of Mapping Idea and Literature Format no. 4(1). 55–73. https://doi.org/10.52970/grmilf.v4i1.351.

Shetu Sabakun Naher. 2023. "Do user-generated content and micro-celebrity posts encourage Generation Z users to search online shopping behavior on social networking sites – the moderating role of sponsored ads". Future Business Journal no. 9. 100. https://doi.org/10.1186/s43093-023-00276-3.

Siregar Yuri, Kent Anthony M., Peirson-Smith Anne Frances, Guan Congying. 2023. "Disrupting the fashion retail journey: Social media and genZ's fashion consumption". International Journal of Retail & Distribution Management no. 51(7). 862–875. https://doi.org/10.1108/IJRDM-01-2022-0002.

Tass Mudasir Ahmad, Malik Irshad Ahmad. 2025. "Driving Environmental Change: The Impact of Social Media on Gen Z's Sustainability Efforts". South Eastern European Journal of Public Health no. XXVI(S1). 623–641. https://doi.org/10.70135/seejph.vi.3639.

Utomo Sasmoko B., Jamali Heni, Arief Ishak, Saputra Muhammad Nabil, Priambodo Candra Gunawan. 2023. "Analysis of The Influence of Hedonic Digital Lifestyle on Consumptive E-Shopping Behavior of Generation Z Through E-Commerce Applications". Jurnal Sistim Informasi dan Teknologi. 85–91.

Venkatesh Viswanath, Thong James Yeong Liang, Xu Xin. 2012. "Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology". MIS Quarterly no. 36(1). 157–178. https://doi.org/10.2307/41410412.

Zhulal Muhammad, Marits Shofi, Herman Sebastian. 2024. "Generation Z purchasing behavior profile in the digital economy: Normative analysis in online markets". Jurnal Ilmiah Manajemen Kesatuan no. 12(1). 1–8. https://doi.org/10.37641/jimkes.v12i1.2326.

Abstract

Social media currently play a key role in the lives of young people, especially in members of Generation Z who have grown up in a digitally connected world. This generation is characterized by a high level of digital literacy, constant online presence and a strong proclivity towards mobile technologies. This paper presents the results of research focused on the attitudes and perceptions of social media in this generation, with a focus on students of Media and Communication Studies in Slovakia. It examines the extent to which factors such as Performance Effort, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Habit, and Behavioral Intention affect perceptions of use of the most widely used social media.

The results of the study provide valuable insights into how Generation Z interacts with social media and what motives drive them to engage in this interaction. Given their impact on the market, the media and social events, this knowledge is significantly beneficial for experts in the fields of marketing communications, media and education.

Keywords: behavioral intention, attitudes, UTAUT2, Generation Z

Tomáš Koprda – His scientific focus is on research in the field of visual communication and design, with an emphasis on packaging and graphic design. He analyzes consumer behavior through eye tracking, examining how visual elements influence decision-making and brand perception. He focuses on optimizing the visual aspects of product packaging to increase product attractiveness and functionality in the market. He applies his research in the commercial and academic sphere in support of the user-centered design.

Milan Džupina – specializes in several areas directly related to the concept of enhancing consumer literacy competencies. Primarily, these include selected areas of marketing management with an emphasis on sustainability and ethical aspects. He lectures on European consumerism where he focuses mainly on identifying new consumer trends and emerging consumer models that shape consumer behavior in the current digital environment.

Györgyi Janková – works at the Department of Mass Media Communication and Advertising at the Faculty of Arts, Constantine the Philosopher University in Nitra, as Associate Professor. Her scientific research focuses on creativity in marketing communication, with a particular emphasis on the identification of message perception by recipients. She analyzes the forms of socially responsible marketing communication, highlighting the socialization, informational and educational functions of the media, and explores marketing communication from the perspective of consumer literacy in children.