

Health, image, and influence: how social media influencers shape consumer behavior in Hungary

Erzsébet Buglyó-Nyakas · Sándor Kovács  · Tímea Gál 

Received: 6 January 2026 / Accepted: 27 August 2026

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Abstract

Social media, electronic word-of-mouth, and influencers are essential parts of our daily lives, all of which have an impact on our shopping habits, consumer decision-making, and health consciousness. The aim of the study on the impact of social media influencers (SMIs) on consumer behavior was to explore the mechanisms of influence among Hungarian consumers, with a special emphasis on health-conscious consumer behavior. The research was based on primary data collection, on a sample of 506 people, representative of gender, age, and type of settlement in Hungary. Confirmatory Factor Analysis (CFA) was used to analyze the data within the framework of a second-order hierarchical model. The results showed that both influencer and social media use have a significant positive impact on shopping behavior, and that influencer credibility is the strongest influencing factor. It is important to note that younger, lower-educated groups with more informal schedules are more receptive to digital recommendations. The research highlighted that Instagram and eWOM (electronic word-of-mouth) have a stronger influence among Hungarian consumers than TikTok. Based on the results, the credibility of an influencer significantly increases trust, which drives emotional attachment and the purchase intention of consumers. The results also highlight the growing importance of authentic interactions and perceived social connections, which are now the driving forces of digital trust. The study provides practical recommendations for the development of targeted marketing strategies.

Introduction

The rise of social media has fundamentally transformed 21st-century communication and decision-making, evolving from simple networking tools into influential marketplaces. Platforms like Facebook, Instagram, and TikTok now host social media influencers (SMIs) who dominate this digital ecosystem. These influencers shape public opinion and consumer behavior through their significant followings, a phenomenon particularly relevant in the health-conscious market where personal recommendations differ from traditional advertising. While idealized content offers inspiration, it carries risks regarding misinformation. This study analyzes the mechanisms through which SMIs influence health decisions, body image, and purchase intentions in Hungary. It seeks to determine how well international trends prevail domestically, how effects vary across demographics, and the role of trust in accepting digital recommendations. The paper reviews literature on eWOM and influencer marketing, defines objectives and hypotheses, details the methodology and results, and discusses findings to better understand Hungarian influencer marketing dynamics.

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Literature review

Social Media and eWOM

Social media has fundamentally transformed how individuals connect and consume information (Gupta et al. 2022), driving adoption of marketing technologies (Eze et al. 2021). Platforms such as Facebook, YouTube, Instagram, Twitter, and TikTok are increasingly popular; Statista (2025) data indicates Facebook was the most used platform in 2025 with nearly 3.07 billion monthly users, followed by Instagram and TikTok. While continuous connectivity serves as a constant stimulus (Lupinacci 2021), research highlights both benefits, like community building (Zhang 2023), and risks, including anxiety and family conflict (Beyari 2023; Wilmer et al. 2017). Despite facilitating connection, social media is linked to mental health challenges and the proliferation of idealized content (Limone and Toto 2021). Social support is crucial, as shoppers often view information from friends as more credible than business sources (Hu et al. 2016; Kelly et al. 2010). However, the lack of non-verbal cues in user-generated content complicates trust-building (Leong et al. 2020), necessitating further studies on social support and trust (Sheikh et al. 2019; Khaw et al. 2022). Technological advances have revolutionized communication (Saura et al. 2021; Behrad 2025), allowing users to share opinions globally and evolving traditional word-of-mouth into electronic word-of-mouth (eWOM) (Tran and Strutton 2020; De Boeck et al. 2022). eWOM extends beyond local circles (Sun et al. 2021), positively influencing social trust (Pang et al. 2024) and purchase intention (Kumar et al. 2023).

The mechanisms and influencing effect of influencer marketing

Today, influencer marketing is an emerging trend (Tao et al. 2019; Abdul Wahab et al. 2024) referring to an eWOM strategy where brands collaborate with influencers to promote businesses (Sokolova and Kefi 2020), a strategy now central to the commercialization of social media stars (Hudders et al. 2021). Influencers act as content producers who shape the attitudes of their target audience to generate profit (Campbell and Grimm 2019; De Veirman et al. 2017; Gräve 2017). The rise of these platforms has created key information sources that influence purchasing through social interactions (Lin et al. 2018; Sheikh et al. 2019), a phenomenon studied by several researchers (Casalo et al. 2018; Jimenez-Castillo and Sanchez-Fernandez 2019; Ki and Kim 2019; De Veirman et al. 2017; Xiao et al. 2018).

A central mechanism of this influence is the credibility and trust. Abdul Wahab et al. (2024) used a PLS-SEM model to demonstrate that influencer credibility significantly impacts followers' parasocial interactions and purchasing behavior. This is supported by Abdul Aziz et al. (2023), who found that credibility influences trust in multichannel marketing and emotional brand engagement. Similarly, Perdana et al. (2023) identified consumer trust as a key mediator between content quality and purchase intentions, where source credibility and disclosure remain paramount (Weismueller et al. 2020). Alwuqaysi (2023) further noted that this social connection fosters emotional support, particularly regarding health and lifestyle choices.

The impact of influencers also extends to efficiency and brand awareness. Al-Zubaidie and Al-Balaghee (2024) observed that influencers effectively guide individuals with busy schedules who avoid extensive information searching. Several studies have shown the positive impact of social media influencers on purchase intent (Gautam and Sharma 2017; Chun et al. 2018; Loureiro and Sarmiento 2019; Saima and Khan 2020). Finally, the landscape is evolving with virtual influencers. Biason et al. (2024) showed that virtual influencer marketing significantly influences product involvement and brand familiarity. These virtual entities are effective in building brand trust and connecting with customers through emotional bonds, demonstrating effectiveness even in specific sectors like the sporting goods industry.

The role of social media influencers in shaping health care decisions

SMIs play a key role in shaping health decisions via platforms like Instagram and TikTok. While Pabian et al. (2025) explore their potential to promote healthy behaviors, they also highlight risks regarding misinformation. Li and Ye

(2025) emphasize the need for media literacy and transparency. Zou et al. (2021) note that audiences prefer narrative evidence over statistical efficacy information. During crises like the COVID-19 pandemic, influencers bridged gaps in institutional trust (Carton-Erlandsson et al. 2025), and healthcare professionals increasingly use these platforms for education (McCausland et al. 2025). Although influencers shape health decisions significantly, the risk of misinformation and the “dark side” of influencer marketing remains critical (Li and Ye 2025; Hudders and Lou 2022; Pabian et al. 2025; Zou et al. 2021; Carton-Erlandsson et al. 2025; McCausland et al. 2025). Consumer trust mediates the relationship between influencers and purchase intentions (Hanna et al. 2020). Consequently, Buglyó-Nyakas and Gál (2025) proposed further research on credibility and health-conscious behavior to fill existing gaps.

Research objectives and hypotheses

Literature highlights the global importance of social media, influencer marketing, and eWOM in shaping consumer behavior, yet gaps remain regarding empirical examinations within the Hungarian context. Consequently, the primary objective of this study is to explore influencer marketing mechanisms among Hungarian consumers, emphasizing online credibility, consumer trust, and purchase intentions. The research seeks to understand the factors determining the success of influencer content and the role of trust. Secondary objectives include examining the mediating role of consumer trust, analyzing the relationship between eWOM and influencer marketing, and formulating practical recommendations for Hungarian professionals to develop effective, trust-based collaborations.

Based on these literature and research goals, several hypotheses were formulated. H1 posits that influencers and social media use positively impact buying behavior; specifically, influence is exerted indirectly through social media use (a), though influencers have a more significant impact on purchase intent than usage frequency (b), with credibility acting as a dominant latent factor in the model (c). H2 suggests that Facebook and TikTok are the most popular platforms. H3 proposes that consumer trust plays a mediating role between influencer marketing exposure and actual buying decisions among Hungarian consumers. H4 assumes significant demographic differences: younger consumers (18–30) are expected to be more affected by visual platforms and influencer attractiveness (a); lower education and income groups may be more susceptible to influence and perceive higher credibility (b); and those with flexible schedules, such as students, are likely more active in influencer-driven shopping than full-time workers (c). Finally, H5 posits that health awareness drives significant behavioral differences, where engagement with influencer products is higher among health-conscious individuals compared to those with lower awareness.

Theoretical Framework

To understand the mechanism of influencer impact, this study utilizes the Stimulus-Organism-Response (S-O-R) model as its primary framework. In the digital commerce environment, influencer content—characterized by informativeness, entertainment, and social presence—serves as a “Stimulus” that triggers internal psychological changes in the “Organism” (the consumer). These changes, such as positive affect, a state of flow, and emotional attachment, ultimately drive the “Response,” which manifests as purchase intention or impulsive buying behavior (Hongsuchon et al. 2025). This process is heavily mediated by Source Credibility Theory, which posits that the effectiveness of a communication depends on the perceived expertise and trustworthiness of the sender (Hovland and Weiss 1951). Influencer marketing has evolved into a structural element of the modern advertising system, fundamentally altering how agencies manage strategic planning and media creativity (Jiménez Marín and Fernandez-Osso Fuentes 2024). This shift is particularly visible in the wellness and “place marketing” sectors, where strategies focus on generating high emotional impact. By aligning product features with consumer happiness, brands create a continuous cycle of consumption where satisfaction is sought through innovative digital engagement (Fernández-Ossó Fuentes and Sánchez-Gey Valenzuela 2024). Furthermore, influencers act as digital leaders who facilitate electronic word-of-mouth (eWOM), providing a more personal and persuasive alternative to traditional corporate messaging (Byrne et al. 2017).

Table 1 Demographic characteristics of the sample ($N = 506$).

Demographic background variables	Frequency (person)	Ratio (%)
Gender		
Female	253	50.0
Male	253	50.0
Age		
18–30 years old	116	22.9
31–40 years old	109	21.5
41–50 years old	132	26.1
above 50 years old	149	29.5
Settlement		
Budapest	92	18.2
City with county rights	107	21.1
Other city	159	31.4
Village	148	29.2

In the specific context of health communication, influencers can promote healthy behaviors but also present significant risks. While some “onco-influencers” provide vital social support and boost self-esteem for patients in niche communities (Cuenca-Octavio and Llorente-Barroso 2023), many others share nutritional advice without professional qualifications. The promotion of “fad diets” by non-experts can lead to nutritional deficiencies and the spread of scientific misinformation (Byrne et al. 2017). This is especially concerning for “digital natives” (children and adolescents), whose interactions with social media are often driven by the Fear of Missing Out (FoMO) and the pursuit of social standing (Elías-Zambrano et al. 2025). Scoping reviews indicate that while influencers build strong trust with adolescents, they frequently promote unhealthy products or unrealistic body images, requiring a focus on media literacy and stricter regulation (Engel et al. 2024). Systematic evidence confirms that exposure to idealized influencer imagery consistently results in body dissatisfaction and anxiety (Powell and Pring 2024). Finally, the labor performed by influencers occupies a complex space between private life and commercial entity, posing unique challenges for labor law and consumer protection (Mangan 2020).

Methodology

Sample of the research and data collection

The research is based on primary data collection, the aim of which was to empirically examine the relationships between the theoretical variables identified in the literature (influencer credibility, parasocial interaction, eWOM, purchase intent) among Hungarian consumers. The data collection was carried out using an online questionnaire at the beginning of 2025. The target group was the Hungarian population aged 18 to 65. The sample size is 506, which is representative of the Hungarian population based on the demographic characteristics of gender, age, and type of settlement. The age group between 18 and 65 years is covered by the widest commercial target group typical of market research. The study was conducted in accordance with the Declaration of Helsinki and approved by the Research Ethics Committee of the Faculty of Economics and Business at the University of Debrecen (Ref. No. GTK-KB 001-3/2025). Prior to accessing the survey, all participants were informed about the study’s purpose and provided written electronic informed consent ensuring anonymity and voluntary participation. The demographic characteristics of the sample are summarized in Table 1.

Table 2 Number of measurement blocks and items used in the questionnaire.

Construct (Latent variable)	Source(s)	Number of items
Social media usage		
Instagram usage	(Abdul Wahab et al. 2024)	4
Facebook usage	(Abdul Wahab et al. 2024)	4
TikTok usage	(Abdul Wahab et al. 2024)	4
eWOM	(Abdul Wahab et al. 2024)	4
Influencer Factors		
Parasocial interaction	(Abdul Wahab et al. 2024)	5
Attractiveness	(Biaison et al. 2024)	4
Trustworthiness	(Biaison et al. 2024)	5
Consumer behavior		
Influencer credibility	(Abdul Wahab et al. 2024)	4
Purchase behavior	(Abdul Wahab et al. 2024)	3
Product involvement	(Biaison et al. 2024)	6
Purchase intention	(Biaison et al. 2024)	5
Buying decision	Al-Zubaidie & Al-Balaghee (2024)	10

Measurement tools and questionnaire structure

The data collection tool for the research was a structured online questionnaire. The first part of the questionnaire assessed the social media usage habits of the respondents. In the second part, respondents were asked to rate different statements adapted from the literature on a 5-point Likert scale (where 1 = strongly disagree, 5 = strongly agree). The statements in the questionnaire were based on previous research by Abdul Wahab et al. (2024), Al-Zubaidie & Al-Balaghee (2024), and Biaison et al. (2024). The constructs used (latent variables) and the number of items measuring them are shown in Table 2.

Methods of data processing

The relationships between items and blocks were explored, and measurement tools were validated using Confirmatory Factor Analysis (CFA). CFA is a special case of Structural Equation Modeling (SEM) (Bollen 1989; Jöreskog et al. 2016) focused on the measurement model (Vandenberg and Lance 2000), which examines relationships between latent factors and observed indicators (Byrne 2013). Unlike Exploratory Factor Analysis (EFA), CFA tests a preliminary theoretical hypothesis rather than deriving structure from data (Brown 2015), offering more reliable results when the theory is established. The method is particularly useful in psychometrics, questionnaire validation, and measuring complex constructs (Kline 2015), allowing for measurement invariance studies across groups (Vandenberg and Lance 2000). Model specification determines the number of factors, variable loadings, and error correlations (Byrne 2013), often visualized via path diagrams.

CFA requires continuous, normally distributed data and careful handling of missing values (Tabachnick and Fidell 2013). Estimating the model involves calculating parameters; Maximum Likelihood (ML) is standard, but robust methods (e.g., MLR) are recommended if normality is unmet (Hair et al. 2018). Model fit is evaluated using indices comparing the model-implied covariance matrix to the sample matrix. The most commonly used fit indices are the *economy index*, calculated as the quotient of Chi-squared (χ^2) and degrees of freedom (df), where a value below 3 indicates an adequate fit; the *Root Mean Square Error of Approximation (RMSEA)*, where a value below 0.06 indicates a good fit and below 0.08 an acceptable fit (Hu and Bentler 1999); and the *Standardized Root Mean Squared Residual (SRMR)*, for which the acceptable value is below 0.08. Furthermore, the *Comparative Fit Index (CFI)* and the *Tucker-Lewis Index (TLI)* are employed to compare the fit of the model to a null model, with values above 0.95 indicating a good fit and those above 0.90 indicating an acceptable fit (Hu and Bentler 1999). Finally, the analysis incorporates the *C90*, which is the 90% confidence interval for the RMSEA value, and *pClose/pFar values*, which

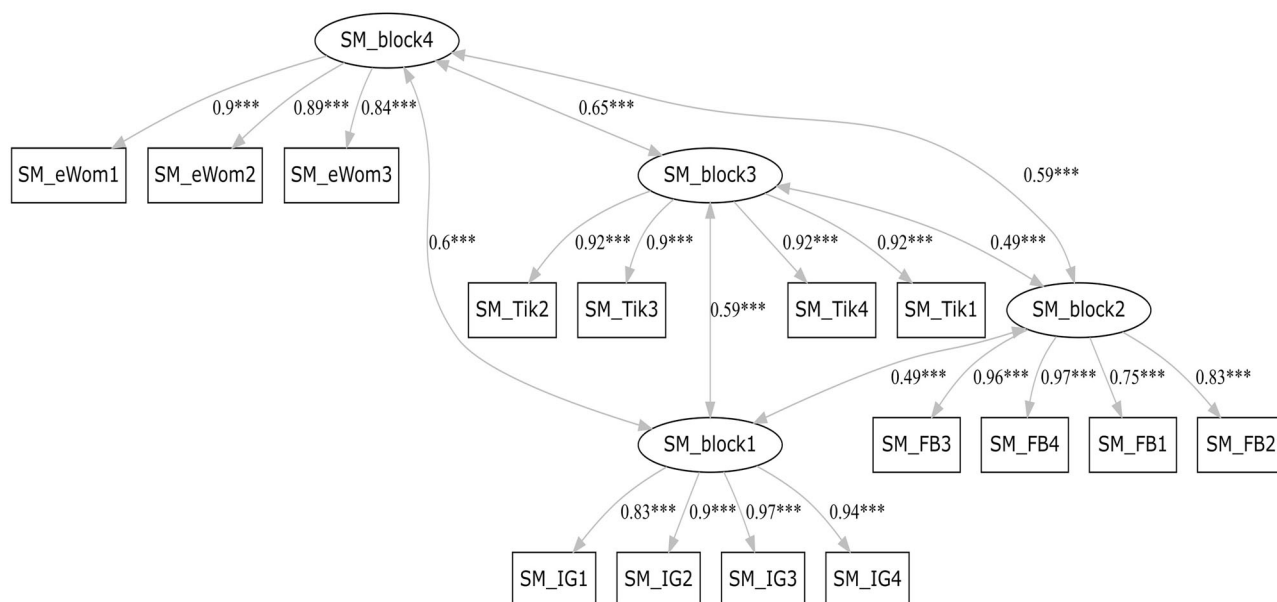


Fig. 1 First-order factor model with multiple correlated factors in media use subblocks (Instagram, Facebook, TikTok, eWOM). See Supplementary Table S1 for the block and variable names Results of the influencer effect block.

represent the probability that the RMSEA is below 0.05 or above 0.08, respectively; a correct fit is confirmed when the C90 contains the value of 0.05 or the entire interval takes values below 0.08. If the model fits poorly, we can modify it based on fit indices and theoretical considerations, provided modifications are always justified on theoretical grounds (Schumacker and Lomax 2012; Marsh et al. 2004). Factor loadings play a key role in interpretation, showing how closely an observed variable relates to a latent one. Standardized loadings range between -1 and +1, indicating the standard deviation change in the observed variable resulting from a change in the latent variable. Hypotheses were tested by examining these standardized factor loadings and the relationships (covariances) between latent variables.

Results

To analyze the data, Confirmatory Factor Analysis (CFA) was conducted within the framework of Structural Equation Modeling (SEM), using the lavaan package in R. The aim of the research was to construct a complex, second-order hierarchical model. This model comprises two levels: at the first level, the individual social media platforms (Facebook, Instagram, TikTok) and eWOM are modeled separately as latent variables, which are captured by a single higher construct, “Social Media Use”, at the second level. A similar hierarchical structure was applied to the main constructs “Influencer Effect” (PI, AT, TR subgroups) and “Purchasing Habits and behaviors” (SMIC, PB, PIN, BD, INT subgroups). The prerequisite for specifying a second-order model is that the number of first-order factors must be at least three, a condition met in all cases in the present study. Prior to specifying the final model, a first-order CFA was performed separately for each main construct in order to validate the substructures. The normality of the variables was examined using the Shapiro-Wilk test, and the condition of multivariate normality was examined with the Energy Test (using the energy package). Due to the violation of the assumption of multivariate normality, the more robust Unweighted Least Squares (ULS) method was used to estimate model parameters instead of Maximum Likelihood (ML) estimation. To determine standard errors and significance levels, 500 bootstrap samples were used. The survey included a total of 63 items; the rate of missing data ranged from 0.4% to 6.7%. Because this rate is considered low, we handled missing data via mean imputation. The fit of the models was evaluated using the following indices: χ^2/df (Chi-squared/degrees of freedom), RMSEA (Root Mean Square Error of

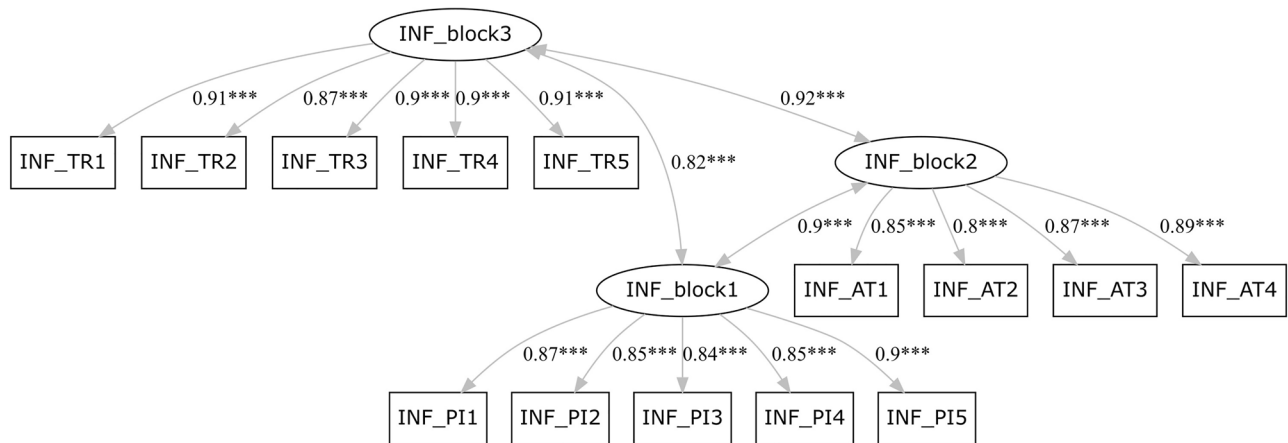


Fig. 2 First-order factor model with multiple correlated factors in the subblocks of influencer effect (PI, AT, TR). See Supplementary Table S2 for the block and variable names. Purchase behavior block results and model fine-tuning.

Approximation), SRMR (Standardized Root Mean Squared Residual), C90 (90% confidence interval for RMSEA), CFI (Comparative Fit Index), and TLI (Tucker-Lewis Index).

Detailed results of first-order CFA models

Media usage block results

Figure 1 shows the CFA model designed for media use. The fit indices of the model were adequate: the value of the Chi-square/df ratio ($\chi^2/df = 211/84 = 2.512$) is less than the threshold value (3), indicating that the fit of the model is adequate. The CFI (0.998) and TLI (0.997) values exceeded the critical 0.95, and the RMSEA (0.055) and SRMR (0.030) values were also lower than the thresholds (0.06 and 0.08). C90 = [0.046, 0.064], pClose was 0.192, and pFar was < 0.001 . Based on this, it can be stated that the theoretical model fits the data well. Most of the factor loadings (standardized values on the one-way arrows) are high and significant ($p < 0.001$), indicating that the individual indicators measure the factor excellently. The strong, significant covariance structure between the factors indicates that the blocks can be summarized into a single higher-order latent variable. The strongest connection was between TikTok and eWOM ($\phi = 0.650$; SE = 0.039; Z = 16.66; $p < 0.001$). Analyzing the factor loadings, it can be seen that in the case of Instagram (block 1), item 3 (“Instagram keeps me so busy that sometimes I completely forget about everything else”) ($\lambda = 0.974$; SE = 0.011; Z = 84.79; $p < 0.001$) and item 4 (“I’m completely immersed in the world of Instagram”) ($\lambda = 0.943$; SE = 0.014; Z = 68.74; $p < 0.001$) are dominant. The same can be said for Facebook (Block 2): item 3 (“Facebook keeps me so busy that sometimes I completely forget about everything else”) ($\lambda = 0.960$; SE = 0.014; Z = 69.13; $p < 0.001$) and item 4 ($\lambda = 0.966$; SE = 0.015; Z = 66.24; $p < 0.001$) were the most dominant.

Figure 2 shows the CFA model developed for the subblocks of influencer effect (Parasocial interaction - PI, Attractiveness - AT, Trustworthiness - TR). The fit of the model was excellent: the value of the Chi-square/df ratio ($\chi^2/df = 121.76/74 = 1.645$) is much lower than the threshold value (3). CFI (0.999), TLI (0.999), RMSEA (0.036), and SRMR (0.032) were all in the range of excellent fit. Significant and high factor loadings indicate that the indicators measure the factor excellently. All of the standardized covariances between the factors were significant, which demonstrates the strong correlation between the blocks and supports the design of the hierarchical model. The strongest relationship was between attractiveness (AT) and trustworthiness (TR) ($\phi = 0.915$; SE = 0.015; Z = 61.95; $p < 0.001$).

Analyzing the factor loadings, it can be seen that the weights are similarly strong across the factors in each block. However, in the case of the parasocial interaction block (PI), item 5 (“How likely are you to talk about an influencer to others?”) carried a relatively higher weight ($\lambda = 0.898$; SE = 0.013; Z = 67.96; $p < 0.001$). In the case of the

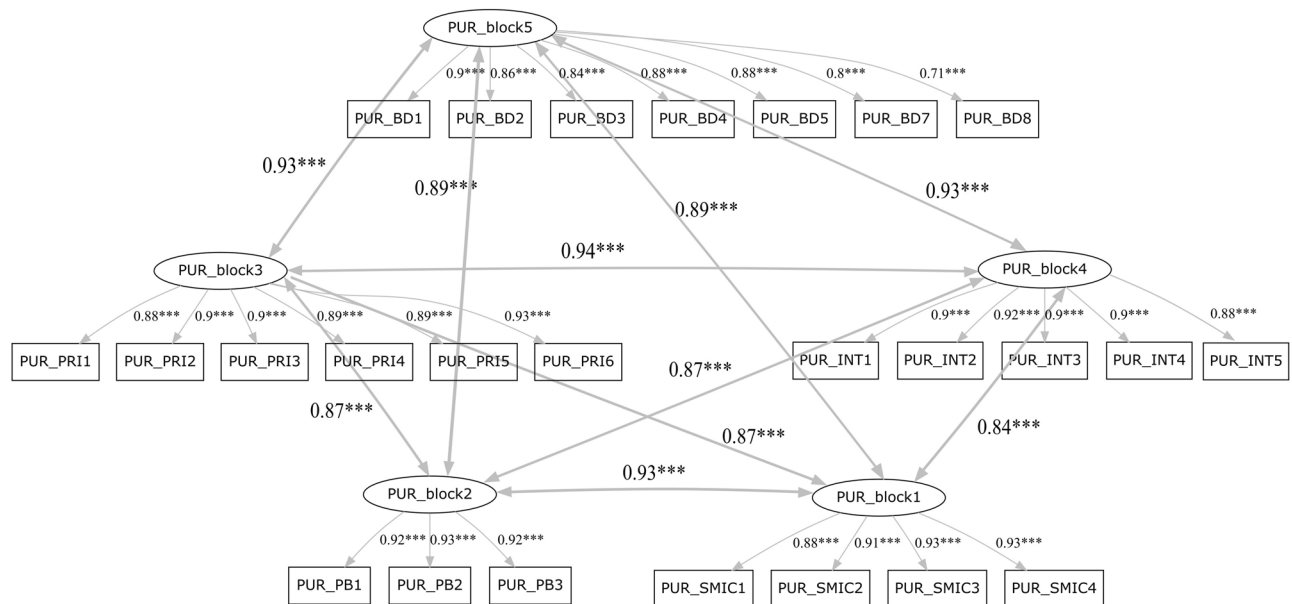


Fig. 3 First-order factor model with multiple correlated factors in subblocks of purchasing behavior (SMIC, PB, PIN, INT, BD) after fine-tuning. See Suppl. Tables S3 and S4 for the block and variable names.

attractiveness block (AT), item 2 (“Do you think an influencer looks good?”) was relatively less connected ($\lambda = 0.800$; $SE = 0.021$; $Z = 38.09$; $p < 0.001$), indicating that respondents associate attractiveness with style and engaging behavior rather than just physical appearance.

Figure 3 shows the CFA model developed for the subblocks of purchasing behavior (Social media influencer credibility - SMIC, Purchasing behavior - PB, Product involvement - PRI, Purchase intention - INT, Buying decision - BD). The original 10-item Buying Decision (BD) specified model showed fit issues. The model was fine-tuned based on theoretical considerations and factor loadings below the threshold of 0.7. Specifically, items 6, 9, and 10 (which asked for information from alternative sources and the opinions of ordinary people) had to be removed from the model. The fine-tuned model has an excellent fit: the Chi-square/df ratio ($\chi^2/df = 167.06/265 = 0.790$) remained well below the threshold value (3). CFI (0.999), TLI (0.999), RMSEA (0.001; $p_{Close} = 0.999$), and SRMR (0.024) were all in the excellent fit range. The mostly significant and high factor loadings ($\lambda > 0.7$) indicate that the indicators measure the factor excellently. All of the standardized covariances between the factors were significant. There was a particularly strong correlation between the willingness to buy (PRI) and the purchase intention (INT) ($\phi = 0.943$; $SE = 0.012$; $Z = 79.39$; $p < 0.001$). Analyzing factor loadings, in the case of the buying decision (block 5), item 1 (“I am influenced by the opinions of the influencers I follow on social media”) determined the factor more significantly (0.897), while items 7 and 8 were relatively less decisive ($\lambda = 0.800$ and 0.711). The strongest factor in the SMIC block was item 4 (“I am inspired by the work ethic and behavior of such an influencer to do the same”) ($\lambda = 0.929$).

In the CFA model, it is theoretically expected that the value of the covariances between the elements within the factors and the elements of the different factors must be zero (unless explicitly allowed). The examination of the modification indices (MI) serves to identify which unspecified relationships would significantly strengthen the fit of the model (threshold $MI > 20$). Based on the examination of the modification indices, it was found that it was not necessary to incorporate further covariances into the first-order models; i.e., the specified theoretical structures reflect the observed data well.

Results of the hierarchical (secondary) CFA model

After the validation and fine-tuning of the first-order multi-factor CFA models, we created the hierarchical CFA model from the first-order factors (Fig. 4). The CFA model for first-order factors was correctly specified, and the

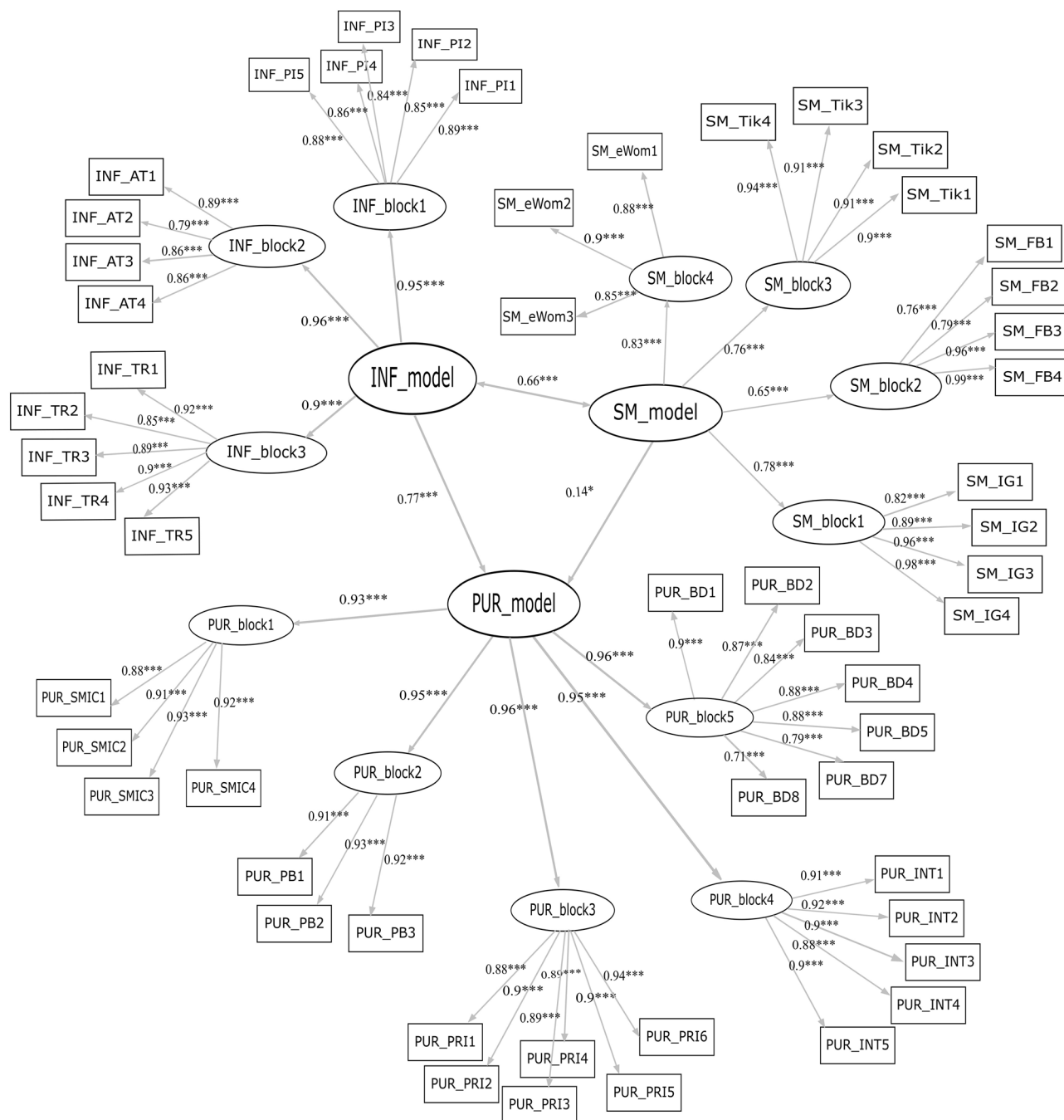


Fig. 4 Hierarchical factor model for the factors of first-order models (Media use, Influencer effect, Purchase intent and behavior). see Supplementary Tables S1, S2, S3, and S4 for the block and variable names. Analysis of second-order factors and their subcomponents.

lavaan package correctly mapped our theoretical ideas about the relationship between variables and factors. The fit indicators of the model are excellent: the value of the Chi-square/df ratio ($\chi^2/df = 1950.40/1310 = 1.489$) is much lower than the threshold value (3). The CFI (0.999) and TLI (0.999) values were above the critical 0.95, and the RMSEA (0.031) and SRMR (0.032) values were also lower than the thresholds (0.06 and 0.08). C90 = [0.028, 0.034], pClose was 1.000, and pFar was < 0.001. Based on this, it can be stated that the entire theoretical hierarchical model fits the data excellently, and the magnitude of standard errors is very small.

The relationships between the second-order factors were all significant and strong. If we analyze the impact on purchase intention and behavior, it can be concluded that the Influencer effect has a more decisive role ($\phi = 0.767$; $SE = 0.048$; $Z = 15.87$; $p < 0.001$) than Media usage ($\phi = 0.142$; $SE = 0.054$; $Z = 2.61$; $p = 0.010$). At the same time, media use also has a significant impact on the purchase. An important finding was that the influence of influencers is also indirectly exerted through the use of social media as a mediator variable ($\phi = 0.655$; $SE = 0.040$; $Z = 16.59$; $p < 0.001$). In other words, the appearance of influencers on social media also encourages more intensive use of social media. Based on the above, we accept both hypotheses H1a and H1b as true. At the same time, based on the results of the influencer block in the model, trust appeared as part of the Trustworthiness (TR) factor. The relationship between trust and purchase decision is supported by high correlations (0.915 between TR and AT) and the main structural pathway (Influencer Effect > Buying). In addition, the influencer effect was also exerted indirectly, through media use, reinforcing the role of mediator variables in the process. Hypothesis H3 has been confirmed. The detailed analysis of the subcomponents of the second-order factors provides an opportunity to evaluate hypotheses H1c and H2.

- Social media use (SM_model): Analyzing the second-order factor loadings, it can be seen that eWOM (SM_block4) determines social media use the most ($\lambda = 0.827$), followed by Instagram ($\lambda = 0.784$) and TikTok ($\lambda = 0.756$), while the role of Facebook was relatively smaller ($\lambda = 0.646$). Based on this, hypothesis H2 was rejected. In general, in the case of Instagram, Facebook, and TikTok, items 3 and 4 (“I’m completely absorbed in the given media,” or “I’m completely immersed in it”) were the most related to first-order factors.
- Influencer effect (INF_model): In this block, all first-order factors were very strongly bound to the second-order factor. The relationship is strongest in the case of attractiveness (INF_block2) ($\lambda = 0.964$) and parasocial interaction (INF_block1) ($\lambda = 0.947$). In terms of attractiveness, (inf_at1) mattered most ($\lambda = 0.893$), and whether the influencer looked good (INF_at2) mattered less ($\lambda = 0.790$). Within the credibility (inf_block3) factor, the credibility item (inf_tr5) received the highest value ($\lambda = 0.927$). This confirms that not only popularity, but also reliability and professional credibility fundamentally determine the influence of influencers on purchases. Based on this, hypothesis H1c was confirmed.
- Purchasing behavior (PUR_model): Here, too, all first-order factors were strongly tied to the second-order factor. The strongest connection was in the case of the buying decision (PUR_block5) ($\lambda = 0.958$), within which the item “I am influenced by the opinions of the influencers I follow on social media” received the most weight ($\lambda = 0.902$).

Finally, the examination of the modification indices for the entire hierarchical model showed that there was no need to modify the model further or impose new covariances, since the value of the indices remained below the threshold of 20, demonstrating the stability and theoretical soundness of the model.

Investigation of CFA components based on background variables

In the following section, we examined the values of validated first-order latent factors (CFA components) across various demographic and background variables (gender, age, education, income, employment status, and health awareness). Since our data did not meet the assumptions of parametric tests (as they were not normally distributed), we used non-parametric tests: the Kruskal-Wallis test to compare three or more independent groups, and the Mann-Whitney test to examine differences by gender. Regarding the gender comparison, there was a significant difference in the use of Facebook (SM_block2) ($Z = -2.203$; $p = 0.028$). Based on the examination of mean scores, men use Facebook less (mean: -0.10) while women use Facebook relatively more often (mean: $+0.10$). The relationship between age and factor values was investigated using Spearman’s correlation coefficient. We found a number of significant negative correlations, suggesting that the younger the respondent, the more characteristic the given behavior or attitude was:

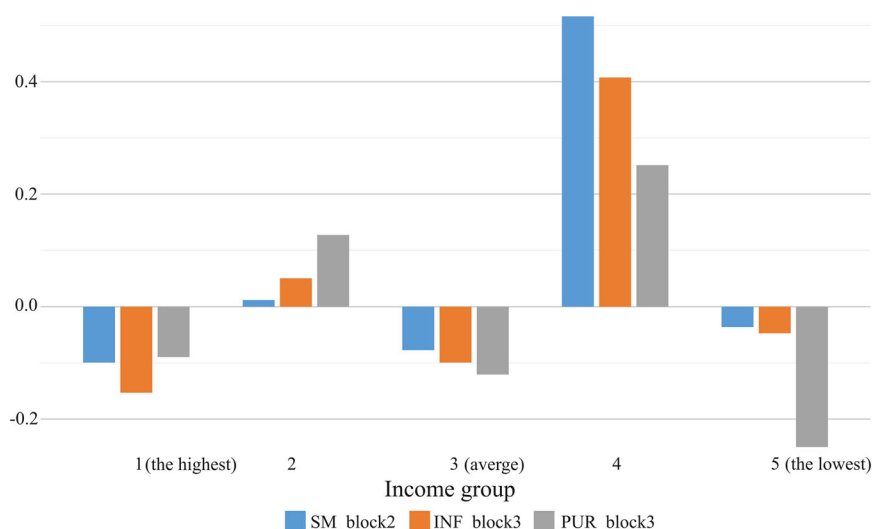


Fig. 5 Mean values of CFA components by income groups. see Suppl. Tables S1, S2, and S3 for the block names.

- Purchasing behavior: All subcomponents of the block were significantly and negatively correlated with age (the correlation coefficients of PUR_block1-5 ranged from $\rho = -0.248$ to -0.266 ; in all cases $p < 0.001$).
- Influencer block: Only parasocial interaction (INF_block1; $\rho = -0.293$; $p < 0.001$) and attractiveness (INF_block2; $\rho = -0.267$; $p < 0.001$) correlated significantly with age.
- Media usage: Instagram (SM_block1; $\rho = -0.334$; $p < 0.001$) and TikTok (SM_block3; $\rho = -0.266$; $p < 0.001$) showed stronger correlations with age. Of all the factors examined, the use of Instagram showed the strongest negative association with age.

Spearman's correlation coefficients showed a clearly negative, significant relationship between age and relevant factors. This demonstrates that the younger age group is more active in using visual platforms and is more receptive to influencer-related factors. Based on this, hypothesis H4a was confirmed. The differences in income status were examined with the Kruskal-Wallis test. There was a significant difference at the 5% significance level regarding Product Involvement (PUR_block3; $\chi^2 = 10.39$; $p = 0.034$), Influencer Credibility (INF_block3; $\chi^2 = 9.92$; $p = 0.042$), and Facebook usage (SM_block2; $\chi^2 = 10.28$; $p = 0.036$). Based on the results (Fig. 5), the second and fourth income groups showed outliers, especially the fourth group (who sometimes do not have enough income to live on). Interestingly, in the case of those who regularly struggle with daily living problems (group 5), product involvement was the lowest.

Table 3 Results of the Kruskal-Wallis test grouped by educational attainment (mean scores).

Factor	Elementary school	Vocational school	Secondary school diploma	Higher education	χ^2 statistics*	p-value
PUR_block1	0.501	0.017	-0.060	-0.058	8.715	0.033
PUR_block2	0.478	0.062	-0.072	-0.086	9.961	0.019
PUR_block3	0.482	0.018	-0.055	-0.062	8.663	0.034
PUR_block4	0.488	0.047	-0.049	-0.103	8.726	0.033
PUR_block3	0.284	0.123	-0.014	-0.186	9.647	0.022
SM_block2	0.299	0.145	-0.068	-0.141	7.845	0.049
SM_block3	0.135	0.250	-0.098	-0.176	8.874	0.031

*Degree of freedom of the χ^2 test (group number - 1) = 3.

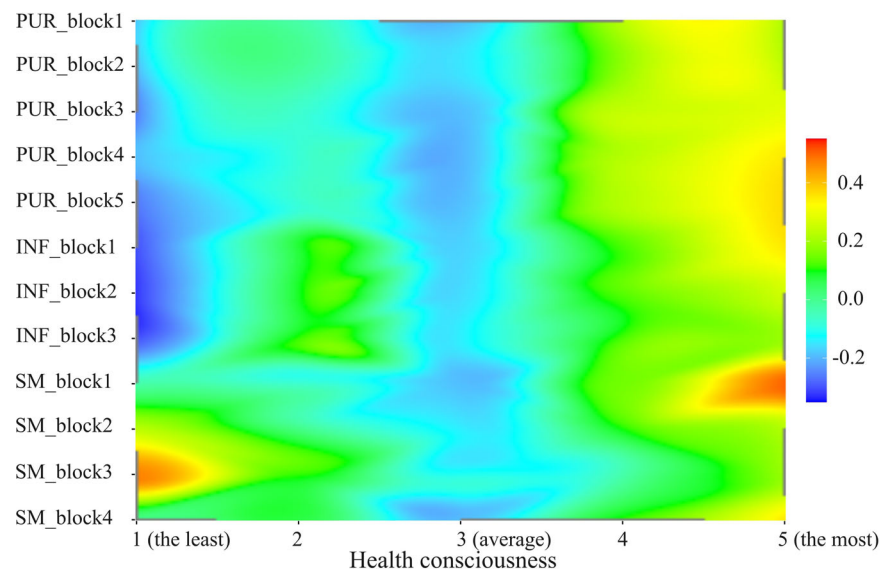
See Supplementary Tables S1, S2, S3, and S4 for the block names.

Table 4 Results of the Kruskal-Wallis test grouped by employment status (mean scores).

Legal status	PUR_block1	PUR_block3	PUR_block5	INF_block2	INF_block3	SM_block3
Active blue-collar worker	−0.061	−0.030	−0.062	−0.069	−0.027	−0.003
Active white-collar worker	−0.068	−0.098	−0.069	−0.075	−0.129	−0.192
maternity leave, dependent	0.398	0.223	0.281	0.282	0.288	0.481
Pensioner	−0.148	−0.109	−0.089	−0.030	−0.082	−0.225
Student	0.218	0.411	0.488	0.421	0.426	0.571
Unemployed	0.210	0.240	0.133	0.178	0.265	0.271
χ^2 statistics*	11.54	11.44	12.29	11.60	15.65	15.28
<i>p</i> -value	0.042	0.043	0.031	0.041	0.008	0.009

*Degree of freedom of the χ^2 test (group number - 1) = 3.

Note: see Supplementary Tables S1, S2, S3, and S4 for the block names.

**Fig. 6** Heat map of the value of CFA components according to health consciousness. see Supplementary Tables S1, S2, S3, and S4 for the block names.

When analyzing the education level, significant differences were observed in purchasing behavior (PUR_block1-4), media use (Facebook and TikTok), and credibility (INF_block3) within the influencer block. The results of the Kruskal-Wallis test and the mean values are summarized in Table 3.

The results showed a consistent pattern: mean values were highest among those with primary education, while for vocational school graduates they were lower**, but still positive. However, values were negative for respondents with a high school diploma or a higher education degree. This suggests that individuals with lower education levels have a higher preference for Facebook and TikTok, are more influenced to buy by influencers, and perceive influencers as more trustworthy. Based on this, hypothesis H4b was confirmed. The differences according to employment status are detailed in Table 4.

Table 4 indicates that those on maternity leave, dependents, the unemployed, and students exhibited significantly positive values on the factors examined, while pensioners showed particularly negative values. The highest values were observed among students (except for SMIC, where dependents scored the highest). The higher activity and receptivity of groups with a more flexible schedule confirmed hypothesis H4c. Examination of the factors according to health consciousness showed differences in almost all cases. Trustworthiness (INF_block3: $p = 0.068$), Facebook usage (SM_block2: $p = 0.092$), and TikTok usage (SM_block3: $p = 0.368$) did not differ significantly according to

health consciousness; however, all other factors did. Figure 6 shows a heat map of the significant factors, where higher values are marked in yellow/red and lower values in blue.

Based on the heat map and significance values (e.g., $p = 0.001$ for PUR_block3 Product Involvement), significantly higher engagement and willingness to buy products recommended by influencers can be observed in more health-conscious groups. Based on this, hypothesis H5 was confirmed.

Discussion

The results of the CFA models suggest that social media influencers (SMIs) exert a significant influence on the purchasing behavior of Hungarian consumers. The research validated theories of digital consumer behavior positing that social interactions and visual stimuli are strong purchasing incentives (Samala and Rawas 2024; An and Ngo 2025). Our finding that influencer credibility is the most decisive factor aligns with the structural importance of influencers in modern digital strategy identified by Jiménez Marín and Fernandez-Osso Fuentes (2024). By applying the S-O-R model, we can see that influencer content acts as a stimulus that triggers an emotional “organism” state—specifically emotional attachment—which then leads to the purchase response (Hongsuchon et al. 2025). The high level of engagement observed in the Hungarian sample mirrors the “happiness-driven” consumption cycles described by Fernández-Ossó Fuentes and Sánchez-Gey Valenzuela (2024), where emotional resonance often supersedes rational product evaluation.

The study also corroborates the research showing that influencers impact consumer decision-making (Shaheen et al. 2025; Balakrishnan et al. 2025). Results demonstrated that both the influencer effect and social media use have a significant positive impact on purchasing behavior, with the former being much more powerful than the mere intensity of media use (Djurica and Mendling 2020; Ramadanty et al. 2020). This suggests consumers make decisions based on personal, credible information rather than solely on the intensity of media consumption. The primacy of credibility in our model supports the classic Source Credibility Theory (Hovland & Weiss 1951), confirming that trustworthiness is the bedrock of digital persuasion. The influencer effect was the strongest explanatory factor in developing purchase intentions, exceeding the direct effect of social media use, consistent with findings by (Sun et al. 2025) and further supported by the insights from Garg and Bakshi (2024), who highlighted the importance of interactional elements used by beauty vloggers in influencing consumer behavior. Notably, the influencer effect impacts purchases not only directly but also through the intensity of media use as a mediator. This means the presence of influencers encourages more intensive platform use, which itself generates purchase impulses; thus, social media functions as both a communication space and a behavior-shaping channel. This observation underpins the integrated functioning of the digital ecosystem highlighted by (Afzal et al. 2024; Nguyen and Nguyen 2025). The research demonstrated that influencer credibility is the most important factor in the influence process; the loading on the Trustworthiness factor was extremely strong. This confirms previous results of other researchers (Khurana et al. 2025; Byrne et al. 2017) and underscores the risks associated with non-qualified influencers sharing unscientific or misleading nutritional advice, which can lead to unnecessary dietary restrictions and potential nutritional deficiencies among the general public.

Regarding platform preferences, eWOM and Instagram dominated influencing factors in the Hungarian sample, while the role of TikTok and Facebook was relatively smaller, differing from international trends (Cruz-Cardenas et al. 2025; Mehta et al. 2025; Reyes-Menendez et al. 2020). Demographic analysis identified additional segments. The younger age group and women constitute the most active target group, especially on Instagram and TikTok (An and Ngo 2025; Ates et al. 2025; Hung et al. 2025). This supports the observations of Elías-Zambrano et al. (2025), who argue that younger “native” consumers use these platforms as a primary tool for identity construction. At the same time, the impact on purchase intentions is weaker in the older age group. Educational attainment is also an influencing factor: those with lower education are more susceptible to influencers (Papadakis et al. 2020; Bellacicco and Pavone 2020). These lower-educated groups’ higher trust in digital recommendations suggests a specific vulnerability to the “unhealthy product promotion” often found in influencer content (Powell and Pring 2024; Engel et al. 2024). Differences in employment status were also significant, with groups having flexible schedules (students, those

on maternity leave) being more active in influencer-driven processes. Finally, marked differences were observed based on health awareness. Among those claiming to be health-conscious, there was a higher level of commitment to recommended products (Khurana et al. 2025). Interestingly, even the least health-conscious group actively used Facebook and TikTok, highlighting the importance of media literacy and misinformation risks.

Overall, this research confirms that influencer marketing is a universal phenomenon, yet local cultural and platform usage differences modify its intensity. For Hungarian consumers, the role of credibility, social support, and eWOM is particularly strong, suggesting that trust and emotional attachment remain the most important drivers of digital influence. The research highlighted that in Hungary, the co-presence of visual content and existing social networks (Instagram, Facebook) continues to have a stronger impact than newer, dynamic platforms. A specific feature of the Hungarian model is that the role of consumer trust is even more pronounced than in international research, indicating a local market characteristic contrasting with global trends. This difference is likely explained by the higher degree of distrust among Hungarian consumers towards advertising, which is partially compensated by the personal communication style of influencers.

Conclusions

The Confirmatory Factor Analysis (CFA) method was employed to explore the complex structure behind social media use, the influencer effect, and consumer purchasing decisions. The data indicate that engagement with both influencers and social media has a significant positive effect on the willingness to buy. This is consistent with digital consumer behavior theories emphasizing the role of personal influence and social proof in the online environment. A key finding is that the credibility of an influencer is a more decisive factor than the mere frequency of platform use. The findings suggest that consumers are more likely to accept recommendations from individuals they perceive as trustworthy and whose communication remains consistent. Therefore, brands should work with influencers who reflect credibility derived not merely from reach but from consumer perception. It is important not only to ask for product endorsements but to allow influencers to present the product in their own voice, building on their stories to strengthen the credibility identified as a high-impact factor.

The CFA results also show that the influencer effect works indirectly through the intensity of media use. Consequently, influencers should be encouraged to engage followers as actively as possible—for example, through live videos, Q&A sessions, or interactive stories. The higher the activity within the platform, the stronger the impact on purchasing. Platform preferences also provided important lessons. In the Hungarian sample, eWOM and Instagram proved to be the strongest influencing channels, while TikTok and Facebook played a relatively smaller role. This suggests classic social media platforms remain dominant, especially among users who are older or possess higher education. Consequently, brands should use different communication styles per platform: on Instagram, visually strong, lifestyle-oriented content works, whereas on Facebook, detailed, information-rich posts are preferred. For TikTok, especially among lower-educated and less health-conscious groups, fast, entertaining content proves effective.

Demographic segments provide further clues. Women and the younger age group are the most responsive target groups, reacting strongly to Instagram and TikTok. For them, short, visually appealing, trend-driven communication is ideal. Conversely, interest in influencers diminishes among older users, so traditional, rational approaches are more effective. For them, Facebook is the right platform, where credibility is strengthened by detailed information and reviews. Educational attainment is also relevant: groups with lower education are more susceptible to influencer-driven incentives and use Facebook and TikTok more often. For them, simple, easy-to-understand messages emphasizing everyday benefits are best. However, for users with higher education, eWOM and Instagram dominate, so content offering professional credibility or quality visuals works best.

Differences based on health consciousness allow for further fine-tuning. Research shows a greater willingness to buy recommended products among health-conscious groups, who prefer Instagram and eWOM. For them, involving expert opinions, detailing ingredients, or presenting lifestyle examples is effective. Less health-conscious groups are

more active on Facebook and TikTok, where emotional or humorous content works well. Overall, the results suggest that a segmented, platform-specific, and credibility-based strategy is essential for effective digital influence.

Based on these findings, several managerial and policy recommendations can be formulated. For marketing professionals in Hungary, the results suggest that “reach” is a secondary metric to “credibility.” Because Hungarian consumers show high distrust toward traditional advertising, brands should prioritize long-term partnerships with influencers who possess genuine professional expertise, especially in the health and wellness sectors. Managers should focus on Instagram and eWOM strategies, leveraging “social presence” and “informativeness” as stimuli to trigger the necessary emotional attachment for purchase. Content should focus on self-esteem and well-being rather than just product utility, as this drives the happiness-based consumption cycles identified in recent literature. From a policy perspective, the findings highlight an urgent need for enhanced regulation of digital health communication. Policy makers should implement stricter disclosure requirements for influencers providing health or nutrition advice, ensuring that those without scientific qualifications are clearly identified. Improving “social media literacy” is essential to protect younger “digital natives” and lower-educated demographics from the negative impacts of idealized body imagery and misinformation. Furthermore, the legal distinction between an influencer’s private life and commercial activity must be clarified to ensure consumer protection laws remain enforceable. The primary limitation of the research is the geographical restriction to a Hungarian sample; future research directions should include studies in other countries to draw widely generalizable conclusions about influencer marketing.

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1057/s41599-026-08960-9>.

Acknowledgements Supported by the University of Debrecen Program for Scientific Publication. Generative artificial intelligence (AI) tools were used to support parts of this research. Google’s Gemini Pro 3.5 large language models was used only to refine the manuscript text. WOS Core Collection’s AI supported research assistant was used for literature search. All outputs produced by these tools were critically reviewed, verified, and edited by the authors to ensure accuracy, originality, and adherence to academic standards. The final responsibility for the content of this article rests entirely with the authors.

Author contributions TG and EB-N conceptualized the study. SK developed the methodology, was responsible for software and visualization. EB-N and SK performed the formal analysis and investigation. EB-N wrote the original draft. TG and SK reviewed and edited the manuscript. TG supervised the project.

Declarations

Competing interests The authors declare no competing interests.

Ethics approval and consent to participate Ethical Approval Name of the approval body: Research Ethics Committee of the Faculty of Economics and Business at the University of Debrecen. Confirmation of standards: We confirm that all research was performed in accordance with the relevant guidelines and regulations, specifically the Declaration of Helsinki. Approval number/ID: GTK-KB 001-3/2025. Date of approval: 25 March 2025. Note: While formal approval was finalized on 25 March 2025, the research design and ethical protocols were reviewed and preliminary clearance was granted prior to the commencement of data collection. Informed Consent How consent was obtained: Informed consent was obtained electronically (written electronic consent) from all participants before they could access the questionnaire. When consent was obtained: During the data collection period in early 2025. By whom and from whom: Consent was obtained by the authors via an online panel system managed by a third-party market research agency from a representative sample of the Hungarian population ($N = 506$, ages 18–65). Procedure: Participants were presented with a “Letter of Consent” (Informed Consent Form) at the start of the online survey. This document detailed the study’s purpose, the voluntary nature of participation, anonymity, and data protection measures. Participants provided their consent by clicking the “Consent” button to proceed. No personally identifiable information (such as names or e-mail addresses) was collected or shared with the authors. The script/text used for this consent process is provided in the Supplementary Information files. All authors have provided full agreement to this submission and consent to be held accountable for all aspects of the work in ensuring that any questions related to the accuracy or integrity of any part of the work are suitably investigated and resolved.

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Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Authors and Affiliations

Erzsébet Buglyó-Nyakas¹ · Sándor Kovács² · Tímea Gál¹

¹ Faculty of Economics and Business, Institute of Rural Development and Functional Management, University of Debrecen, Debrecen, Hungary

² Faculty of Economics and Business, Coordination and Research Centre for Social Sciences, University of Debrecen, Debrecen, Hungary