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SOCIAL INFLUENCE AS A DETERMINANT OF MOBILE APPLICATION ACCEPTANCE ACROSS GENERATIONS: A POLISH PERSPECTIVE

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Abstract: *The widespread diffusion of mobile devices has made mobile applications an integral part of everyday life across age groups. Although prior research has consistently identified social influence (SI) as an important determinant of technology acceptance, its role across different generations remains insufficiently examined in the context of mobile applications. This study investigates the impact of social influence on behavioural intention to use mobile applications among four generational cohorts: Baby Boomers, Generation X, Generation Y, and Generation Z. The analysis is based on data from a nationwide CAWI survey conducted in Poland (N = 2,400; 600 respondents per generation). Reliability analysis, exploratory factor analysis, linear regression, and comparative statistical tests were applied. The results show that social influence is a significant predictor of behavioural intention in all generational groups. However, no statistically significant differences are observed in the strength of the SI–BI relationship across generations. At the same time, significant differences emerge in perceived levels of social influence, with Baby Boomers reporting higher mean values than younger cohorts. The findings highlight generational differences in the perceived relevance of social influence rather than in its behavioural impact, contributing to research on human–technology interaction.*

Keywords: *social influence, mobile application, technology acceptance; behavioural intention; generations; human–technology interaction*

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INTRODUCTION

Smartphones and mobile applications have evolved from communication tools into socio-technical environments that mediate everyday activities, shape user practices, and transform human-technology interaction patterns. Contemporary research emphasises that mobile applications operate not only as functional technologies but as socially embedded systems that influence cognition, behaviour, and mediated communication (Leonardi, 2021; Norman, 2013) This broader framing is essential for aligning the study with the scope of Human Technology, which prioritises conceptualisations of technology that extend beyond utilitarian adoption.

Although social influence (SI) is a well-established determinant of technology acceptance, prior findings on generational differences remain fragmented and theoretically inconsistent. Some studies report diminishing SI effects among younger, digitally autonomous users (Carter & Yeo, 2016), whereas others highlight the rising importance of digitally mediated SI such as peer-generated reviews, influencers, and algorithmic visibility,which may exert comparable influence across age groups (Sözer, 2020; Tran & Vu, 2024). This tension points to a broader theoretical gap concerning generational differences in socio-technical mechanisms of social influence and their implications for behavioural intention. Addressing this ambiguity positions the present study within current debates in human-technology interaction.

The past decade has witnessed a substantial increase in the use of mobile devices, particularly smartphones, which have become integral to everyday life (Huang & Kao, 2015). As of 2025, 5.78 billion people globally use a mobile phone, representing 70.5% of the world's total population. Over the past 12 months, the number of unique mobile subscribers has grown by 112 million, reflecting a year-on-year increase of 2.0%. Furthermore, smartphones now account for nearly 87% of all mobile handsets in use worldwide (DataReportal – Global Overview, 2025). In Poland, 96% of individuals aged 16 to 64 own a smartphone, and the number of active cellular mobile connections in early 2025 reached 53.7 million equivalent to 140% of the total population. This figure is influenced by individuals owning multiple devices (DataReportal – Digital 2025: Poland, 2025). Smartphones have evolved beyond their original purpose of voice communication, transforming into multifunctional mobile computing devices that facilitate a broad spectrum of activities. Today, they are widely used in professional settings, entertainment, communication, and healthcare (Ma et al., 2016).

Mobile applications, as one of the most rapidly evolving digital products, play a crucial role in shaping this transformation. In 2023, global spending on mobile applications rebounded, reaching 171 billion USD (Statista - Mobile Internet & Apps, 2024). In Poland, the mobile application market generated 753.37 million USD in revenue, reflecting a significant increase compared to previous years. The highest revenues were recorded in the categories of gaming (241.7 million USD) and social media (196 million USD), while shopping (65.99 million USD) and entertainment applications (57.75 million USD) also contributed substantially to market expansion (Sirant & Kucia, 2024). These figures highlight the continuous growth of the mobile app economy, driven by technological advancements that are reshaping interactions between businesses and consumers (Payne & Frow, 2017).

Designed for use on smartphones and tablets, mobile applications have increasingly become a pivotal element in business strategy, serving as a powerful marketing tool (San-Martín et al., 2016). Their widespread adoption has garnered considerable attention from enterprises (Nah et al., 2005), positioning these digital solutions as innovative platforms for communication and customer relationship management. The transformative impact of mobile applications is particularly evident in the evolving dynamics of business-consumer interactions (Viswanathan et al., 2017). However, fully leveraging the benefits of mobile applications requires a comprehensive understanding of user behavior and the factors influencing technology acceptance.

The growing prevalence and diversification of mobile applications have significantly altered user behaviors (Juaneda-Ayensa et al., 2016), emphasizing the necessity of systematic academic inquiry in this area. Existing literature highlights that the rapid development of digital communication technologies, including mobile applications, often surpasses the pace of rigorous scientific validation (Boudreaux et al., 2014; Vahdat et al., 2021). Consequently, empirical research aimed at understanding user motivations and behavioral patterns in adopting mobile technologies remains a critical endeavor.

Over years of research, multiple determinants have been identified as influential in technology acceptance theories. One of the key factors consistently linked to the intention to use digital information systems and mobile applications is social influence (SI) (Alam et al., 2018; Boontarig et al., 2012; Martins et al., 2021; Sun et al., 2013; Wills et al., 2008). Social influence is defined as the extent to which individuals perceive that significant people in their lives (e.g., family, friends) believe they should adopt a specific technology (H. Peng et al., 2019; Venkatesh et al., 2012). This factor has been highlighted in various technology acceptance models, including the Theory of Reasoned Action (TRA) (Taylor & Todd, 1995), the Technology Acceptance Model (TAM) (Venkatesh & Davis, 2000), the Extended Technology Acceptance Model (TAM2) (Lu et al., 2005), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh et al., 2012). Given the growing significance of public opinion in contemporary society, it is essential to examine its role in mobile application adoption.

Literature suggests that age-related differences play a crucial role in the acceptance of new communication technologies (ICT), including mobile applications. However, findings in this area remain inconclusive. Some studies indicate that social influence is more pronounced among younger individuals due to peer pressure dynamics (Carter & Yeo, 2016). In contrast, other studies highlight the increasing reliance on external opinions among individuals with lower technological competence, who often depend on the skills and recommendations of those around tchem (Muñoz-Leiva et al., 2017; Schierz et al., 2010).

Considering the identified research gap and the lack of comprehensive studies on this subject in the Polish market, this research aims to examine the impact of social influence on mobile application adoption. Specifically, the study will assess the strength of social influence among representatives of different generational cohorts: Baby Boomers, Generation X, Generation Y, and Generation Z. Understanding generational variations in technology acceptance is crucial for businesses and policymakers seeking to develop effective digital strategies tailored to different demographic groups.

LITERATURE REVIEW

The place of social influence in the theory of technology acceptance

Technology acceptance research has historically emphasized utilitarian determinants, primarily perceived usefulness and perceived ease of use as central predictors of technology adoption. However, behavioral science and psychology consistently demonstrate that adoption is also driven by non-utilitarian drivers such as social norms, identity signalling, interpersonal expectations, and social image (Ajzen & Fishbein, 2002; Triandis, 1971, 1980). These elements shape how individuals interpret and respond to technological innovations.

Social influence (SI), defined as the degree to which an individual perceives that significant others believe they should use a system, has been recognized across multiple decades of technology acceptance research (H. Peng et al., 2019; Venkatesh et al., 2003, 2012). Diffusion-of-innovation theory highlights that individuals turn to social cues to reduce uncertainty about novel technologies, relying on both informational and normative pressures (Peng et al., 2017; Rogers, 2003; Salancik & Pfeffer, 1978). As uncertainty declines, the role of SI typically shifts but does not disappear.

Across foundational frameworks: TRA, TPB, TAM2, IDT, MPCU, UTAUT, SI appears under varying conceptual labels (subjective norm, social factor, image) but consistently reflects the influence of external expectations on behavioral intention (Garavand et al., 2019; Karahanna et al., 1999; Lewis et al., 2003). In UTAUT, SI is a primary determinant of intention, moderated by age, gender, and experience. UTAUT2 further extends this recognition to voluntary contexts, demonstrating that SI remains a relevant factor even when users are free to adopt or reject a technology (Venkatesh et al., 2012).

Taken together, prior research clearly establishes SI as a positive predictor of behavioral intention. Thus, we propose:
H1: Social influence (SI) has a positive impact on behavioral intention (BI) to use mobile applications across all generations.

Generational dynamics in social influence: socio-technical mechanisms underlying age differences

Age-related differences play a crucial role in shaping technology-related behaviors, yet empirical findings remain mixed. Younger users (Millennials, Generation Z) have grown up in a digitally dense environment, where technology use is individualized, exploratory, and often detached from direct interpersonal pressure (Carter & Yeo, 2016). Their high digital literacy reduces reliance on external validation, and their adoption choices are frequently shaped by digitally mediated forms of SI, such as peer-generated reviews, influencers, and algorithmically curated trends (Sözer, 2020; Tran & Vu, 2024). For these groups, SI tends to be subtle, embedded in digital ecosystems, and intertwined with identity expression.

In contrast, older generations (Generation X, Baby Boomers) often rely more heavily on direct interpersonal SI in technology adoption (Blok et al., 2020; Hoque & Sorwar, 2017). Limited digital confidence, heightened perceived complexity, and lower technological autonomy result in a greater need for reassurance from trusted individuals (Muñoz-Leiva et al., 2017; Schierz et al., 2010). For this group, SI functions as both a facilitatorwhen encouragement is present and a barrier when social networks express skepticism (Soh et al., 2024). Older adults are also more likely to rely on face-to-face, trust-based social cues rather than digital forms of influence (Webster & Trevino, 1995).

This indicates that generational differences in SI stem not merely from demographic variation but from distinct socio-technical contexts, including:

- disparities in digital literacy and autonomy,
- reliance on interpersonal vs. digital social cues,
- differences in perceived technological risk,
- divergent expectations regarding technology's role in daily life.

Given these distinctions, SI may operate through qualitatively different mechanisms across generations. Therefore:

H2: The impact of social influence (SI) on behavioral intention (BI) to use mobile applications varies across generations.

Integrating Human-Technology Interaction Perspectives

In line with the expectations of Human Technology, SI must be conceptualized not only as interpersonal pressure but as a socio-technical process shaped by digital affordances, mediated communication, and contemporary hybrid interaction environments (Leonardi, 2021; Norman, 2013). Mobile applications increasingly function as socially embedded technologies, enabling visibility, comparison, recommendation, and social signalling within digitally mediated ecosystems (Boyd & Ellison, 2007; Faraj et al., 2018; Korjonen-Kuusipuro & Wojciechowski, 2022, 2023). As a result, SI emerges through layered mechanisms offline interpersonal cues and online platform-based cues rather than a single normative channel (Leonardi & Treem, 2020).

Existing technology acceptance models (TRA, TAM, UTAUT) capture only partial aspects of this complexity. These frameworks were developed in contexts characterized by more stable and less digitally mediated social structures, where social influence was primarily conceptualized as subjective norms or direct interpersonal pressure(Ajzen & Fishbein, 2002; Davis, 1989; Venkatesh et al., 2003). Contemporary digital ecosystems, however, introduce algorithmically curated influence, asynchronous communication, and decentralized online sociality, which are not explicitly addressed in traditional acceptance models (Kellogg et al., 2020; Leonardi, 2021). Therefore, a contemporary interpretation of SI should incorporate these socio-technical affordances rather than treat social influence as a purely interpersonal construct.

This broader framing suggests that Baby Boomers may rely more strongly on direct interpersonal mechanisms of social influence, such as family members, peers, or trusted professionals, while younger users navigate digitally embedded forms of SI, including platform visibility, online reviews, and peer activity cues (Cimperman et al., 2016; Muñoz-Leiva et al., 2017). Importantly, this distinction does not necessarily imply stronger statistical effects of SI on behavioural intention (BI) among older adults. Instead, it reflects differences in the mechanisms and channels through which social influence is experienced and enacted, rather than differences in effect magnitude (Leonardi & Vaast, 2017).

Building on this distinction between generational mechanisms of social influence, the following hypothesis focuses on differences in the nature and mode of influence, rather than its statistical strength:
H3: Baby Boomers may rely more heavily on interpersonal social influence mechanisms than younger generations; however, this does not necessarily imply a stronger SI → BI effect.

METHODS

The study on the impact of social influence on the acceptance of mobile applications was conducted using the CAWI method via the Manulo professional research panel. The research complied with Polish quality standards for public opinion and market research (PKJPA). Measurement items were adopted from established scales reported in prior studies. In total, 12 items were included in the analysis, seven measuring Social Influence (SI) and five measuring Behavioral Intention (BI). All items were assessed using a five-point Likert scale.

Data collection was carried out in August 2023. A control question regarding the use of mobile applications was applied, and only respondents who declared using mobile applications at least several times per year were allowed to participate in the survey. The study employed a quota-based sampling design. The final sample consisted of 2,400 respondents, with 600 individuals in each generational cohort: Baby Boomers, Generation X, Generation Y, and Generation Z (Table 1). The gender structure of the sample reflected the distribution of the Polish population (52% female and 48% male).

Table 1. Sample size [Source: own research, 2023]

Generations	Gender		N
	Female	Male	
Baby Boomers	312	288	600
Gen X	312	288	600
Gen Y	312	288	600
Gen Z	312	288	600
SUM	**1248**	**1152**	**2400**

To avoid regional bias, the survey was conducted across all Polish voivodeships. The sample included respondents from rural areas, small towns, and large cities with more than 500,000 inhabitants, representing diverse educational backgrounds and professional statuses.

Statistical analyses were conducted using the Statistical Package for the Social Sciences (SPSS). The analytical procedure consisted of three stages. First, data screening was performed to assess missing values and potential outliers. Second, scale reliability and validity were evaluated using Cronbach's alpha and exploratory factor analysis (EFA). Third, the relationship between the independent variable (SI) and the dependent variable (BI) was examined using regression analysis conducted separately for each generational group.

RESULTS

Test reliability using Cronbach's Alpha coefficient

Scale reliability was assessed using Cronbach's alpha coefficient. Following established guidelines, a Cronbach's alpha value of 0.70 or higher was considered indicative of acceptable internal consistency (Hair, 2010; Nunnally & Bernstein, 1994). Reliability was examined separately for the independent variable (Social Influence, SI) and the dependent variable (Behavioral Intention, BI), reflecting the conceptual distinction between the constructs.

In addition to Cronbach's alpha, corrected item–total correlations were analysed to evaluate the contribution of individual items to their respective scales. Values above 0.30 were regarded as satisfactory, indicating adequate item discrimination (Nunnally & Bernstein, 1994).

Table 2. Reliability statistics of SI and BI variables [Source: data analysis]

	Cronbach's Alpha	N of Items
SI	0.815	7
BI	0.843	5

As reported in Table 2, both scales demonstrate good internal consistency, with Cronbach's alpha values of 0.815 for SI and 0.843 for BI. Item–total statistics presented in Table 3 show that all items exceed the recommended threshold for corrected item–total correlation. These results confirm that the measurement scales for both SI and BI are reliable and suitable for further analysis.

Table 3. Item-Total Statistics of SI and BI variables [Source: data analysis]

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SI1	17.05	17.995	0.659	0.773
SI2	17.20	18.158	0.631	0.777
SI3	17.49	18.238	0.584	0.785
SI4	17.05	19.255	0.482	0.803
SI5	17.16	18.537	0.568	0.788
SI6	17.18	18.367	0.605	0.782
SI7	16.68	20.565	0.354	0.823
BI1	13.88	9.657	0.632	0.816
BI2	14.23	9.513	0.695	0.798
BI3	14.02	9.390	0.687	0.800
BI4	14.33	10.313	0.587	0.827
BI5	14.37	9.905	0.643	0.813

EFA analysis for independent and dependent variables

Exploratory factor analysis (EFA) was conducted to assess the construct validity of the measurement scales. The suitability of the data for factor analysis was evaluated using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. A KMO value above 0.70 and a statistically significant Bartlett's test ($p < 0.05$) were considered indicative of adequate factorability (Hair, 2010). In addition, factors with eigenvalues greater than 1 were retained, and factor loadings of 0.50 or higher were regarded as acceptable.

EFA was first performed for the independent variable, Social Influence (SI). The initial analysis included seven items; however, item SI7 exhibited an unsatisfactory factor loading and was therefore removed in line with established recommendations. The subsequent analysis, based on six items, met all evaluation criteria. The KMO value was 0.876, and Bartlett's test of sphericity was statistically significant ($p < 0.001$), confirming the adequacy of the data for factor analysis. The total variance explained reached 53.325%, exceeding the recommended threshold. All retained items loaded above 0.50 on a single factor, indicating satisfactory convergent validity.

A separate EFA was conducted for the dependent variable, Behavioral Intention (BI). The results also met all required criteria. The KMO value was 0.840, Bartlett's test of sphericity was significant ($p < 0.001$), and the total variance explained amounted to 61.483%. All BI items demonstrated factor loadings above 0.50, supporting the unidimensionality of the scale.

The final component matrix for both SI and BI variables is presented in Table 4. Overall, the EFA results confirm that the measurement scales exhibit adequate construct validity and are suitable for subsequent regression analysis.

Table 4. Component Matrix of SI and BI variables [Source: data analysis]

Variables	SI1	SI2	SI3	SI4	SI5	SI6	BI1	BI2	BI3	BI4	BI5
Component	0.787	0.774	0.741	0.609	0.712	0.744	0.771	0.820	0.813	0.734	0.780

Regression analysis of the relationship between SI and BI

To examine the relationship between social influence (SI) and behavioural intention (BI), simple linear regression analysis was conducted. Given that the model included one independent variable (SI) and one dependent variable (BI), separate regression models were estimated for each generational cohort: Baby Boomers, Generation X, Generation Y, and Generation Z. All analyses were performed using SPSS 22.

Model adequacy was assessed using the F-statistic derived from the ANOVA table. As shown in Table 5, the regression models are statistically significant across all generational groups ($p < 0.001$), indicating that the models provide an adequate fit to the data.

Table 5. ANOVA test of generation groups [Source: data analysis]

Generation		Model	Sum of Squares	Df	Mean Square	F	Sig.
Baby boomers	1	Regression	63.444	1	63.444	137.312	0.000
		Residual	276.301	598	0.462		
		Total	339.745	599			
Generation X	1	Regression	37.731	1	37.731	81.771	0.000
		Residual	275.931	598	0.461		
		Total	313.662	599			
Generation Y	1	Regression	47.236	1	47.236	96.902	0.000
		Residual	291.504	598	0.487		
		Total	338.741	599			
Generation Z	1	Regression	53.689	1	53.689	115.829	0.000
		Residual	277.183	598	0.464		
		Total	330.872	599			

Regression coefficients for each cohort are reported in Table 6. In all generational groups, the standardized regression coefficient for SI is positive and statistically significant ($p < 0.001$), indicating that higher levels of perceived social influence are associated with stronger behavioural intention to use mobile applications. The standardized beta coefficients range from 0.347 to 0.432, suggesting a moderate relationship between SI and BI across generations.

Table 6. Regression coefficient of generation group [Source: data analysis]

Generation	Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
			B	*Std. Error*	*Beta*			*Tolerance*	*VIF*
Baby boomers	1	(Constant)	2.754	0.099		27.863	**0.000**		
		SI	0.375	0.032	**0.432**	11.718	**0.000**	1.000	1.000
Generation X	1	(Constant)	2.468	0.111		22.203	**0.000**		
		SI	0.355	0.039	**0.347**	9.043	**0.000**	1.000	1.000
Generation Y	1	(Constant)	2.332	0.113		20.674	**0.000**		
		SI	0.396	0.040	**0.373**	9.844	**0.000**	1.000	1.000
Generation Z	1	(Constant)	2.292	0.111		20.573	**0.000**		
		SI	0.430	0.040	**0.403**	10.762	**0.000**	1.000	1.000

Collinearity diagnostics indicate no multicollinearity concerns, as variance inflation factor (VIF) values remain well below the commonly accepted threshold (Hair, 2010). Based on the estimated coefficients, standardized and unstandardized regression equations for each generational group are reported in Table 7.

Table 7. Regression coefficients for BI [Source: data analysis]

Generation	Unstandardized regression equations	Standardized regression equations
Baby boomers	$BI = 2.754 + 0.375SI + \varepsilon$	$BI = 0.432SI + \varepsilon$
Generation X	$BI = 2.468 + 0.355SI + \varepsilon$	$BI = 0.347SI + \varepsilon$
Generation Y	$BI = 2.332 + 0.396SI + \varepsilon$	$BI = 0.373SI + \varepsilon$
Generation Z	$BI = 2.292 + 0.430SI + \varepsilon$	$BI = 0.403SI + \varepsilon$

Overall, the regression results confirm that social influence is a significant predictor of behavioural intention to use mobile applications in all analysed generational cohorts.

Differences in the SI–BI relationship and perceived social influence across generations

To examine whether the impact of social influence (SI) on behavioural intention (BI) differs across generational groups, pairwise comparisons of regression coefficients were conducted using the procedure proposed by Paternoster et al. (1998). This approach allows for statistical testing of differences between regression slopes by accounting for both coefficient estimates and their standard errors.

The results of the Z-tests are reported in Table 8. Across all pairwise comparisons between Baby Boomers, Generation X, Generation Y, and Generation Z, the obtained p-values exceed the conventional significance threshold ($p > 0.05$). These findings indicate that there are no statistically significant differences in the strength of the SI–BI relationship across generational groups.

Table 8. Z test results between generations [Source: data analysis]

Generation		Z-test	p-value
Baby boomers	Generation X	0.396448	0.345887
	Generation Y	0.409956	0.340919
	Generation Z	1.073695	0.858520
Generation X	Baby boomers	0.396448	0.345887
	Generation Y	0.733900	0.231505
	Generation Z	1.342500	0.089717
Generation Y	Baby boomers	0.409956	0.340919
	Generation X	0.733900	0.231505
	Generation Z	1.342500	0.089717
Generation Z	Baby boomers	1.073695	0.858520
	Generation X	1.342500	0.089717
	Generation Y	0.601041	0.273906

In addition to slope comparisons, differences in the perceived level of social influence across generations were examined using one-way analysis of variance (ANOVA). As shown in Table 9, the ANOVA results reveal a statistically significant effect of generation on perceived social influence ($F = 16.880$, $p < 0.001$), indicating that mean SI scores differ across generational cohorts.

Table 9. ANOVA test of SI between generations [Source: data analysis]

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	28.366	3	9.455	16.880	0.000
Within Groups	1342.089	2396	0.560		
Total	1370.455	2399			

Post-hoc multiple comparison tests were conducted to identify the specific group differences (Table 10). The results show that Baby Boomers report significantly higher levels of perceived social influence compared to Generation X, Generation Y, and Generation Z ($p < 0.001$ for all comparisons). No statistically significant differences in perceived social influence were observed among Generations X, Y, and Z.

Table 10. Post-hoc comparisons of SI between generations [Source: data analysis]

(I) Generation	(J) Generation	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Baby boomers	Generation X	**0.223**	0.043	**0.000**	0.14	0.31
	Generation Y	**0.256**	0.043	**0.000**	0.17	0.34
	Generation Z	**0.266**	0.043	**0.000**	0.18	0.35
Generation X	Baby boomers	-0.223	0.043	**0.000**	-0.31	-0.14
	Generation Y	0.034	0.043	**0.437**	-0.05	0.12
	Generation Z	0.043	0.043	**0.319**	-0.04	0.13
Generation Y	Baby boomers	-0.256	0.043	**0.000**	-0.34	-0.17
	Generation X	-0.034	0.043	**0.437**	-0.12	0.05
	Generation Z	0.009	0.043	**0.827**	-0.08	0.09
Generation Z	Baby boomers	-0.266	0.043	**0.000**	-0.35	-0.18
	Generation X	-0.043	0.043	**0.319**	-0.13	0.04
	Generation Y	-0.009	0.043	**0.827**	-0.09	0.08

Figure 1 presents the mean levels of perceived social influence for each generational group. Consistent with the ANOVA results, Baby Boomers display the highest mean SI values, while the remaining generations show relatively similar levels of perceived social influence.

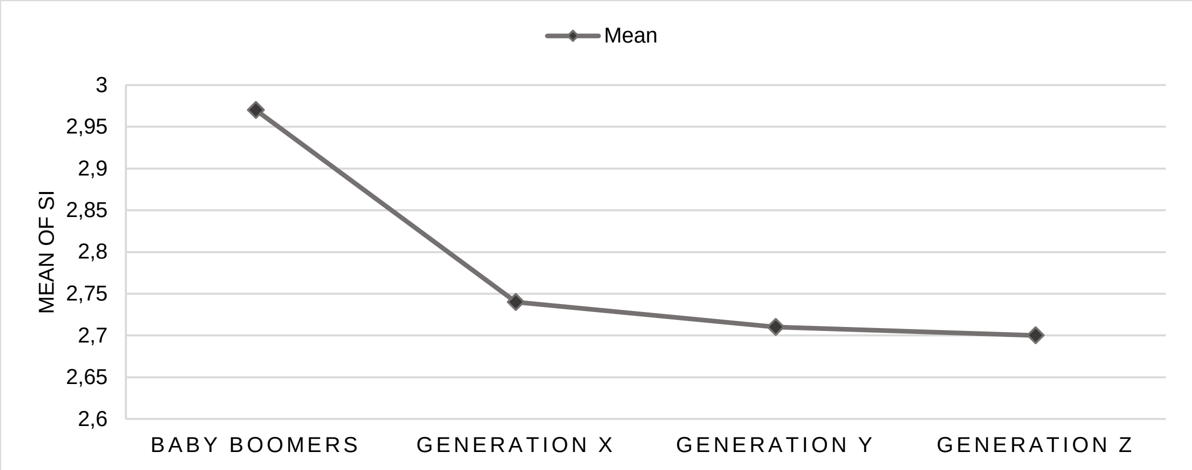

Figure 1. Mean levels of perceived social influence across generations. [Source: data analysis]

DISCUSSION

This study examined the role of social influence (SI) in shaping behavioural intention (BI) to use mobile applications across four generational cohorts in Poland. The results provide clear support for the central premise that SI is a significant and positive predictor of BI in all analysed generations, thereby supporting H1. Across Baby Boomers, Generation X, Generation Y, and Generation Z, SI consistently exhibited a statistically significant relationship with BI, with standardized coefficients ranging from moderate to moderately strong.

At the same time, the comparative analyses indicate that the strength of the SI-BI relationship does not differ significantly across generations. Although the standardized regression coefficients vary numerically between cohorts, the Z-tests reveal no statistically significant differences in slopes. Consequently, H2, which posited generational variation in the impact of SI on BI, is not supported in terms of effect size. This finding is theoretically important, as it suggests that social influence remains a robust determinant of mobile application acceptance regardless of generational affiliation, even in an era of widespread digital familiarity (Chaouali et al., 2016; Martins et al., 2021). At the same time, prior research indicates that the relative importance of social influence and other acceptance determinants may vary across national and cultural contexts, suggesting that these findings should be interpreted within the specific socio-cultural setting of Poland (Alkailani & Nusairat, 2022).

Importantly, the absence of significant differences in regression coefficients should not be interpreted as evidence that social influence operates identically across generations. The additional ANOVA and post-hoc analyses demonstrate significant differences in mean levels of perceived social influence, with Baby Boomers reporting higher SI than Generations X, Y, and Z. These results indicate that while SI exerts a comparable impact on behavioural intention across cohorts, its salience and experiential relevance differ by age group (Cimperman et al., 2016; Muñoz-Leiva et al., 2017). In other words, generational differences are more apparent in how strongly SI is perceived and valued, rather than in how effectively it translates into behavioural intention. Recent empirical evidence confirms that social influence continues to play a meaningful role in contemporary mobile application contexts, including mental health applications evaluated using the UTAUT2 framework (Malik & Mushquash, 2025).

From a human-technology interaction perspective, this distinction is critical (Leonardi, 2021; Norman, 2013). For older users, social influence appears to be more closely tied to interpersonal mechanisms, such as recommendations from family members, peers, or professionals, which help reduce uncertainty and compensate for lower digital confidence. For younger users, SI is more likely to be embedded in digitally mediated environments, including online reviews, platform visibility, and social media cues, even if these forms of influence are perceived as less salient at a conscious level. This interpretation aligns with prior research showing that younger generations often rely on platform-based and algorithmically mediated signals rather than direct interpersonal persuasion (Tran & Vu, 2024).

Taken together, the findings refine existing UTAUT-based research by demonstrating that generational differences in mobile application acceptance are not primarily a matter of stronger or weaker effects, but of differing socio-technical mechanisms through which social influence is experienced and enacted (Leonardi, 2021; Venkatesh et al., 2012). This contributes to the Human Technology literature by highlighting the importance of distinguishing between the presence, perceived relevance, and mode of operation of social influence in technology adoption processes.

Despite the contributions of this study, several limitations should be acknowledged. The analysis is based on cross-sectional survey data and simple linear regression models estimated separately for generational cohorts. While this approach enables transparent and interpretable comparisons, it does not capture more complex structural relationships or latent interactions that could be examined using advanced modelling techniques such as multi-group structural equation modelling. In addition, the model focuses on social influence in isolation from other UTAUT-related determinants, which constrains its explanatory scope. Finally, although the sample is large and nationally representative, the findings are embedded in the Polish socio-cultural context and should not be directly generalized to other settings without caution.

CONCLUSIONS

This study provides empirical evidence that social influence is a significant and positive determinant of behavioural intention to use mobile applications across generational cohorts in Poland. The results confirm that SI plays a meaningful role in mobile application acceptance for Baby Boomers, Generation X, Generation Y, and Generation Z alike. Contrary to some expectations in the literature, the strength of the SI–BI relationship does not differ significantly across generations, suggesting a stable role of social influence in contemporary mobile technology adoption (Chaouali et al., 2016; Martins et al., 2021).

At the same time, the study reveals clear generational differences in perceived levels of social influence. Baby Boomers report higher sensitivity to SI compared to younger cohorts, indicating that social context and interpersonal reassurance remain particularly salient for older users (Cimperman et al., 2016; Muñoz-Leiva et al., 2017). These findings underscore the importance of differentiating between statistical effect size and subjective relevance when interpreting generational patterns in technology acceptance.

By integrating large-scale empirical evidence with a human–technology interaction perspective, the study advances understanding of how social and technological factors jointly shape mobile application adoption (Leonardi, 2021; Norman, 2013). Rather than framing generational differences in terms of stronger or weaker effects, the results point to variations in the socio-technical forms through which social influence is encountered, interpreted, and acted upon.

IMPLICATIONS FOR RESEARCH, APPLICATION, OR POLICY

From a research perspective, the findings suggest that future studies should move beyond simple comparisons of effect sizes across demographic groups and focus more explicitly on the mechanisms through which social influence operates in digitally mediated environments. Incorporating constructs related to digital affordances, platform design, trust cues, and algorithmic visibility may provide a richer understanding of how SI is embedded in human–technology interaction. Longitudinal and mixed-method approaches could further clarify how reliance on different forms of social influence evolves with experience and technological change.

For practitioners and application developers, the results highlight the need to recognise generational differences in the form rather than the strength of social influence. For older users, facilitating interpersonal support and providing clear, trustworthy guidance may enhance adoption, particularly for applications related to essential services such as healthcare, banking, or public administration. For younger users, attention should be given to usability, transparency of platform cues, and the integration of socially mediated signals within digital ecosystems, rather than relying on direct interpersonal persuasion.

From a policy perspective, the findings support initiatives aimed at promoting digital inclusion and reducing age-related barriers to technology use. Policies that encourage accessible design, user support mechanisms, and digital literacy programmes may help ensure that mobile technologies are adopted equitably across age groups. At the same time, policymakers should remain attentive to how social influence is embedded in digital platforms, particularly with regard to transparency, data protection, and the potential vulnerabilities of older users in socially mediated digital environments.

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