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The Always-Connected Consumer: A Study On Consumer Habits And Smart Interactions

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Abstract: *In today's world, where the digital environment shapes everyday life, understanding smart consumers and their use of technology becomes essential for analysing digital consumption behaviour. Thus, this study aims to investigate the technology consumption of generations Y and Z, focusing on how they use devices connected to the Internet of Things. The research is based on a quantitative method, using an online questionnaire that generated 195 valid responses, and the data analysis focused on the differences between generations and genders in terms of time spent online, the number of influencers followed, and the types of devices predominantly used. Accordingly, statistical analyses such as regressions, t-tests, one-way ANOVA, and factor analysis were applied. The results highlight a correlation between the type of activities carried out and the preferred environment: people who spend more time online tend to carry out multiple activities in this space, while individuals who are more active offline show a marked preference for offline activities. Furthermore, Generation Y tends to adopt technology from a pragmatic perspective, while for Generation Z it represents a source of entertainment and socialisation. In particular, these findings contribute to a better understanding of the behavioural differences between Generations Y and Z in the context of technology consumption and IoT adoption.*

Keywords: *digital consumption; digital connectivity; digital engagement; IoT; consumer usability; media consumption; digital media; generation Z; generation Y; AI devices.*

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1. Introduction

For 21st century consumers, their online behaviour is increasingly shaped by the constant evolution of digital technologies and the implications of artificial intelligence, while the amount of time spent browsing is growing in tandem with new online developments (Arbanas et al., 2024). In other words, modern consumers use the Internet for various daily activities, such as socialising and gathering information, but also for professional activities directly related to their workplace, although transformed through the lens of digital characteristics (Atzori, Iera, & Morabito, 2010; Zak & Hasprova, 2020).

Moreover, the number of active participants in the virtual environment stands at approximately 5.56 billion people, accounting for more than half of the global population, namely 67.9%. In addition, according to statistics from February 2025, this connectivity is reflected in the rapid growth of Internet-connected devices, with 97.8% of Internet users over the age of 16 owning and frequently using a smartphone (Datareportal, 2025). Statista Research Department (2016) stated that by 2025, there would be over 75 billion smart devices connected to the Internet, which would make people's lives more efficient. Therefore, the integration of these smart technologies is increasingly sought after by modern consumers, as they manage to streamline their activities and, at the same time, perform multiple tasks or interactions with people, these data being influenced by digital information networks (Lynn et al., 2022).

Accordingly, in June 2024, users spent an average of eight hours navigating their digital activities, with the benefits perceived by them becoming apparent every day (Arbanas et al., 2024). In addition, in March 2025, one in five online consumers is expected to spend at least 4.5 hours each day using their mobile phone (Bufe, 2025). This reinforces the modern consumer's need for access to devices that are ready to translate their behaviour online, while also emphasizing the importance of rapid and accessible communication. In this way, the experience of modern consumers is enhanced by interaction styles representative of electronic devices, but also by advanced user interfaces that offer, first and foremost, accessibility (Benvenuti et al., 2021).

In other words, we are in a period where the ability to connect with other people or information no longer depends entirely on a computer or mobile phone, but relies on a wide range of other smart devices designed to make users' daily lives easier. Accordingly, the concept of the Internet of Things stands out, increasingly shaping the lifestyle of modern consumers towards virtual experiences (Atzori, Iera, & Morabito, 2010; Miorandi et al., 2012). In fact, these digital solutions are supported by both artificial intelligence and information and communication technologies, creating new possibilities for individuals in terms of digital evolution (Chukwudi et al., 2023).

In particular, the relationship that modern consumers have with the digital environment and the defining elements of the Internet lay the foundation for new forms of behaviour, as their experiences are increasingly altered by the virtual and artificial intelligence-based nature of daily activities. Thus, it is essential to understand the interactions that users have with smart devices and, more importantly, to analyse their habits in this digital age in order to offer them personalised solutions and technologies. In regard to this, the present study offers a current perspective on how modern consumers use technology, marking the time spent online, the digital activities performed, but also the main smart devices used. Therefore, it is operationalised through a multi-faceted framework: (O1) identifying links between time spent online and influencer engagement, (O2) examining generational and gender-based differences in digital usage, and (O6) mapping the relationship between smart devices and specific online activities. As these aspects shape the behaviours of 21st century users, both digital marketers and social science researchers may benefit from the study's findings regarding consumers' decisions and preferences influenced by the Internet and modern technologies. Accordingly, the findings contribute to the theoretical expansion of the literature on digital consumer behaviour and the evolving IoT landscape and also offer valuable insights for digital marketers and technology developers about consumer-oriented solutions aligned with modern behavioural needs and preferences of 21st users.

2. Theoretical Framework

User behaviour has changed over time depending on how they consume online content and, ultimately, how information is presented. In light of this context, the Internet is becoming the main tool that users employ in obtaining and circulating data and information, materialising as an essential part of everyday life (Chen, 2020; Kania-Lundholm, 2023). Thus, most individuals prefer to transpose their habits in relation to electronic devices, relying increasingly on their connectivity and ability to be both mobile and connected to a network (Alam, 2018). In this way, user behaviour is reshaped by the constant digitisation of their environment, with the Internet and smart devices becoming a powerful pillar in their daily interactions.

Consequently, modern technologies, in tandem with artificial intelligence and its characteristics, manage to integrate into users' activities and thus influence their daily actions and attitudes (Atzori, Iera, & Morabito, 2010). Through these intelligent processes, recorded data are processed automatically, with various devices independently collecting and transforming information in order to present it to users in an enhanced form (Paschen, Kietzmann, & Kietzmann, 2019; Kong et al., 2022). Thus, technologies based on the Internet of Things manage to design a much more satisfying version of life for individuals (Miorandi et al., 2012; Wilson, Hargreaves, & Hauxwell-Baldwin, 2015), where embedded smart objects create a comfortable and much more efficient environment in terms of living and services provided (Atzori, Iera, & Morabito, 2010; Kong et al., 2022). In other words, the modern consumer is characterised by their degree of connectivity with the online environment, but also by the activities carried out predominantly in this space.

The literature also emphasises that smart technologies are no longer just an advantage for certain people, but are becoming a necessity, a fundamental pillar in the lives of individuals in the 21st century (Verizon, 2025). Therefore, adapting to IoT systems denotes an increase in the quality of life of individuals (Dong et al., 2017), from creating a safer space to streamlining daily activities. For this reason, the integration of digital networks with various physical objects, such as devices, buildings, smart vehicles, but also programs and sensors, results in the exchange of information between them and, implicitly, streamlines the consumer's lifestyle (Dong et al., 2017; Alam, 2018). Respectively, the communication of these connected devices lays the foundation for decisions and actions that are different from those made by humans, which are carried out according to the information obtained, shared, and interpreted by artificial intelligence in the form of algorithms (Statista Research Department, 2016; Bolton et al., 2018; Van Deursen et al., 2021). In particular, studies note an increase in the adoption of these smart devices, namely 42-45% in the United States, with smart doorbells and thermostats being the most preferred objects (Verizon, 2025). In this regard, we emphasise that the network of objects that defines the Internet of Things is composed of a wide range of smart devices connected to the Internet (Chui, Löffler, & Roberts, 2010; Riggins & Wamba, 2015), including those used on a daily basis, such as mobile phones and devices that individuals can carry with them (Van Deursen et al., 2021), as well as televisions and tablets (Kim, 2021). In addition, there are devices that help streamline household activities, namely smart meters (Statista Research Department, 2025), as well as industrial devices that monitor healthcare or urban infrastructure (Riggins & Wamba, 2015).

In this context, access to information and various options related to commerce, social platforms, or reviews weigh considerably in terms of the purchasing or consumption behaviour of the modern user (Mutoni, 2025). In this sense, consumption no longer refers only to the act of purchase, but also extends to viewing and interacting with online content, as mediated by the smart objects used. Thus, a current study highlights the consumption of video games, not only as an activity of playing, but also of participating in or watching the respective videos, with approximately 80% of players and 85% of consumers currently interacting in some form with these activities (Newzoo, 2024). Moreover, it is noteworthy that these modern users consume multiple types of online content, all of which are found in the virtual time portfolio, such as streaming video, music, podcasts, or gaming content (Widener et al., 2025).

In particular, a significant feature of the Internet of Things is its interconnectivity, with a network existing between smart objects, individuals, and the environments in which they are used, whether we are talking about networks in different spaces or distributed in a single room, such as lights or heat (Wilson, Hargreaves, & Hauxwell-Baldwin, 2015). In other words, it creates the possibility of communication between these entities, laying the foundations for a synergy in which each element interacts with each other, facilitating the lives and behaviours of modern consumers (Hakvoort, Beale, & Ch'ng, 2013; Riggins & Wamba, 2015; Kim, 2021; Kania-Lundholm, 2023). Smart technologies facilitate everywhere connectivity (Atzori, Iera, & Morabito, 2010), exemplified by smartphones that provide persistent, secure, and faster interaction with other networked objects to enhance functionality (Hakvoort, Beale, & Ch'ng, 2013; Wilson, Hargreaves, & Hauxwell-Baldwin, 2015). By enabling these everyday essential objects to communicate with one another, an improved, interconnected environment can be created, both at home, when travelling, at work or during other physical activities (Atzori, Iera, & Morabito, 2010). In addition, most offline activities, i.e., traditional activities, are increasingly intertwined with the online environment, with users choosing to browse social media platforms, engage in recreational activities such as digital games, or simply purchase products from various websites (Madden & Jones, 2008). In fact, studies highlight that once a social connection is established, modern consumers increase their online activity by 30% (Althoff, Jindal, & Leskovec, 2017), thereby spending more time browsing and performing virtual actions compared to previous years (Lut et al., 2021). In other words, the more content there is online, the more time users will spend browsing the Internet (Chen, 2020).

In particular, modern technologies influence consumer behaviour in terms of the digital spaces where time is spent browsing, thus mentioning media consumption. Hence, since access to information and documentation in general is influenced by changes in digitisation, users choose to consume content over which they have control in terms of the type and manner in which they consume it (Weingartner, 2021; Alzub, 2023), but also in terms of when they choose the content (Alzubi, 2023).

In the same manner, the rising importance of the online sphere and, implicitly, of social media platforms is significantly changing the media ecosystem (Johnson & Sandström, 2022), giving rise to new ways of promoting content, such as influencers. In tandem with the evolution of digital technology, influencers post advantageous information about products or services, becoming a common feature in the lives of modern consumers (Zak & Hasprova, 2020). Moreover, contemporary social media engagement is shaping new approaches to attracting potential buyers, namely the integration of artificial intelligence into the analysis and design of marketing strategies, thereby enabling more personalized content (Beyari & Hashem, 2025). In fact, there has been a significant increase in the features integrated by AI and, more than that, in its actual use, which outlines its new role in consumers' lives, namely influencing their decisions (Duan, Edwards, & Dwivedi, 2019).

Beyond algorithms and systems (Vlačić et al., 2021), modern consumers perceive artificial intelligence as an adaptive intelligence that replicates human behaviour (Duan, Edwards, & Dwivedi, 2019) and optimizes decision-making to maximize situational success (Chukwudi et al., 2023). In fact, these digital solutions have succeeded in creating a much more comfortable environment for users (Kim, 2021), who rely on the constant evolution of technologies to shape their lives (Chukwudi et al., 2023). In particular, the use of AI stands out by simulating consumer desires, being able to understand what they want and, implicitly, to offer them intelligent solutions based on their emotions, motivations, and habits (Kim, 2021). In other words, we are talking about 21st century users who transpose their actions and behaviours into the online environment, focusing on the benefits in terms of connectivity, but also on the ease of carrying out certain actions.

Although we can easily highlight the amalgam of benefits felt with the incorporation of modern technologies, smart devices, and artificial intelligence-based systems, it is necessary to also mention the disadvantages that arise with their excessive use. In other words, the literature increasingly points out that the primary use of the online environment can create digital addiction (Fan et al., 2025) and, implicitly, a lack of availability in users' physical lives, where studies show that various tasks are neglected in favour of surfing the Internet (Milková, Kaliba, & Ambrožová, 2022; Frielingsdorf et al., 2025) or maintaining interpersonal relationships (Arbanas et al., 2024). In fact, the more time spent on a smartphone, the greater the risk of depression (Zhu et al., 2025). In addition to the mental health problems that we can associate with these trends, depression and anxiety, there are also physical problems, such as lack of sleep (Yu et al., 2024; Frielingsdorf et al., 2025). Here, we also mention muscle problems caused by prolonged poor posture (Arbanas et al., 2024; Zhu et al., 2025).

Furthermore, literature shows that young people tend to be more affected by this digital addiction than older generations (Milková, Kaliba, & Ambrožová, 2022) and, in addition, Generation Z and millennial participants are more concerned about the negative aspects of excessive online consumption, such as harmful content, as well as health and physical problems (Arbanas et al., 2024).

3. Methodology

In terms of the research approach incorporated in this paper, a quantitative method based on a data collection instrument, namely a questionnaire, was employed. Distributed online, the questionnaire sought to record relevant responses from active users in the virtual space of the Internet who use various smart devices in their daily lives. In other words, the data were collected using the survey method to ensure efficient data gathering and facilitate statistical analysis (Bryman, 2016). Moreover, the theme of our study encompasses digital technology and its current relevance, and thus, the online distribution of questions facilitated the achievement of a representative sample for our target population, namely active digital users.

The study focused on quantifying digital habits by examining time allocation in virtual environments, activity-based distribution, and the level of technology implemented in everyday life. Another aspect examined was the relationship that 21st century users have with online-connected devices. In terms of the type of questions, the tool was built on the basis of closed-ended scales and was structured into several representative sections. Thus, we mention questions related to online activities, from social media to information and recreation, but also segments dedicated to the devices used and the integration of IoT into everyday life. Finally, demographic data designed to better understand the modern user and their predisposition to adapt to changes in modern technologies was also included.

In this way, the purpose of the study is to analyse generational differences between Generation Y and Generation Z in the context of Internet of Things usage, exploring how device preferences and online interaction patterns reflect distinct attitudes towards technology and digital services.

Also, according to the literature and the research direction, we propose the following objectives and hypotheses:

O1. Identifying the links between the variables: time spent online, time spent following influencers, and the number of influencers followed. (H1 and H2 are derived)

O2. Identifying differences in time spent online from the perspective of consumer generation and gender. (H3 and H4 are derived)

O3. Determining the dimensions in which consumer activities are divided. (derives H5)

O4. Determining the most used devices on the phone according to generation.

O5. Identifying the offline activities most representative of the target population.

O6. Identifying the links between smart devices and consumers' online activities.

To further explore this topic, we propose the following hypotheses to help us establish a consensus on modern consumers and their behaviour:

H1. There is a positive correlation between the number of influencers followed and the time spent online.
H2. There are statistically significant associations among time spent following influencers, time spent online, and the number of influencers followed.
H3. There are differences between generations in terms of the time consumers spend online.
H4. There are differences between genders in terms of the time consumers spend online.
H5. The activities recorded by consumers are divided into two representative factors, online and offline, with significant correlations.

As we wanted to collect a relevant database to verify the proposed hypotheses, the online questionnaire was active for a longer period of time, namely December 2024 – March 2025. During this period, a conventional non-probabilistic sampling strategy was used, suitable for online research, which provided us with a representative sample in terms of the necessary practical criteria (Etikan, Musa, & Alkassim, 2016).

In total, there were 204 registered respondents, but only 195 of them completed the questionnaire, with nine users being excluded. In other words, the minimum age for inclusion in the research was 18 years, with participants falling within the 1981–1996 range, users belonging to Generation Y, and between 1997–2013, users belonging to Generation Z. In this regard, our research recorded 84 people belonging to Generation Y (43.1%) and the remaining 111 representatives of Generation Z (56.9%). Additionally, before analysing these digital behaviours, study participants were assessed using a preliminary scale that measured each online user's level of smart consumerism. This scale sought to identify the extent to which individuals exhibited informed, responsible, and technology-oriented behaviour, which are defining characteristics of a modern consumer (Jelea et al., 2025).

Although a smart consumer may have a number of characteristics, including active information gathering, critical evaluation of information, and responsible actions, the concept has a broader scope in today's digital context. Namely, the modern consumer has multiple roles in the digital consumer environment, adapting their processes and daily life to modern models and technologies (Ahn, 2020). In fact, the results collected indicate that respondents can be defined as smart consumers who have a much higher adaptability to digitisation and, implicitly, an increased integration of modern technologies into various aspects of everyday life.

This is reinforced by the questionnaire itself, where 70.6% of participants say they use their mobile phone to coordinate or control other digital devices. Although there are differences between the generations analysed, most respondents are familiar with technology and have a constant online presence, according to their recurrent use of smart devices, which describes them as digital natives (Prensky, 2001; Panagiotou, Lazou, & Baliou, 2022).

The composition of the sample does not differ greatly in terms of the gender of the people who responded to the questionnaire, with both women and men in balanced numbers, namely 97 female respondents and 98 male respondents. Since the sample is relatively evenly divided, we can conclude that the interpreted results provide a realistic idea of the differences between genders and reflect behaviour representative of individuals who spend time online.

Moreover, in terms of time spent online, with an emphasis on socialising through virtual spaces, we can say that most participants do so to a fairly high degree. Thus, more than half of the respondents, namely 105 people, claim that they spend more than 50% of their time on this activity. Comparatively, we can say that people who are part of Generation Y spend less time than people from Generation Z, a statement that can be seen in Table 1, where there are differences between the two generations for each percentage spent socialising online.

In particular, the trend observed shows an increase in Generation Z respondents as time spent in the digital environment increases, and an increase in Generation Y respondents as time spent decreases. Similarly, there were three participants who claimed to spend 0% of their time socialising online, all of whom were part of Generation Y.

Moreover, the data presented in Table 1 indicate a stronger inclination towards online engagement among the younger generation, a finding consistent with existing literature showing that younger individuals interact more extensively with virtual environments and digital media (Mutoni, 2025).

Accordingly, being exposed to digital devices to a greater extent throughout their lives (Prensky, 2001), young people will be predisposed to spend more time online, a statement also supported by the higher interconnectivity ranges mentioned in the table. Thus, Generation Z becomes dominant in terms of time spent online, with 60% of 19 respondents from Z compared to 6 from Y, 80% with 8 users from Z compared to 2 from Y, and 100%, where there are 4 respondents from Z compared to a single participant from Y. In other words, modern consumers who are part of Generation Y have adapted to some extent to current technologies and the development of digitalisation, but those in Generation Z are much more prepared, as the online environment has been integrated into their social lives much earlier.

Table 1. Number of participants per generation and their time spent online

Nr. crt.	Percentage corresponding to online socialising	Number of respondents	Number of Y Generation respondents	Number of Z Generation respondents
1	0% time spent	3	3	0
2	10% time spent	19	13	6
3	20% time spent	18	11	7
4	30% time spent	31	12	19
5	40% time spent	19	5	14
6	50% time spent	30	16	14
7	60% time spent	25	6	19
8	70% time spent	27	13	14
9	80% time spent	10	2	8
10	90% time spent	8	2	6
11	100% time spent	5	1	4
Total number of respondents		195	84	111

In fact, in terms of the occupation of the digital users who participated in the study, we can say that the majority are students, accounting for approximately 29.75% of the entire sample, where n = 58, but immediately below them are those working in IT, with 15.38%. This confirms the respondents' orientation towards younger generations, who are also those who resonate much better with digital media. Therefore, Figure 1 shows the distribution of the sample according to place of work.

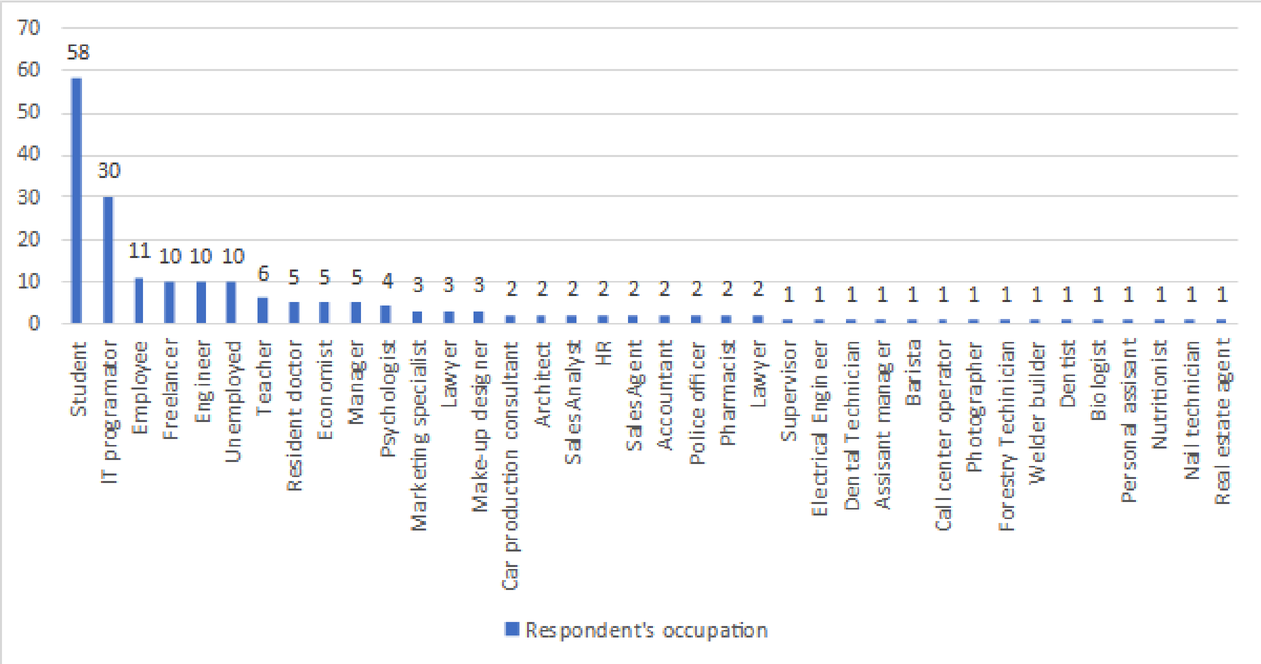

Figure 1. Distribution of the respondents' sample according to workplace (Source: own processing)

Next, we note the second place, where IT programmers are located, followed by participants whose profession involves knowledge of digital skills, the IT field (n = 30) and the liberal professions (n = 10) involving a relatively constant digital presence. There are also less representative categories, such as photographers, architects, lawyers, or accountants, but they still outline a profile of the modern consumer, connected to digital technologies and smart tools.

Regarding the origin of respondents, we can mention that the sample consists of individuals located in different geographical areas of the country, in cities representative of Romania's university centers. Thus, there is a contextual diversity of smart consumers in Iași, Bucharest, Cluj-Napoca, and Timișoara, which provides the study with a variation in terms of digital behaviour and the use of modern technologies. Therefore, the geographical distribution contributes to a more comprehensive observation of the digital consumption of Generation Z and millennial users.

The data analysis method consisted of preparing a database compatible with the IBM SPSS Statistics v.20 statistical program, which helped us obtain complex analyses, comparisons, and defining elements in achieving our objectives (Arkkelin, 2014). Thus, the data volume was processed and techniques such as descriptive analyses and Pearson correlations were used to measure the strength and direction between two quantitative variables (Cohen et al., 2013). In addition, exploratory factor analysis was employed to identify and group correlated variables into common factors, thereby enhancing the understanding of consumer behaviour (Costello & Osborne, 2005). Furthermore, analysis of variance (ANOVA) was used to determine whether statistically significant differences existed between three or more independent groups (Howell, 2012; Field, 2018). This article chooses to focus only on connected devices, sensors, connectivity networks, and user applications because these components are the most visible to consumers and directly shape how IoT value is experienced. While other elements of the IoT ecosystem, such as cloud platforms, data management, and cybersecurity are also essential, they operate largely in the background. Our intention was to concentrate on the aspects that most strongly influence consumer interaction, perception, and adoption.

Having this in mind, the variables we will interpret in this study are focused on the actual interaction of consumers with the digital environment, starting with time spent online, time spent following influencers, the number of influencers followed, but also online activities and, of course, offline activities. In other words, "time spent online" represents the average daily duration, calculated in hours, during which respondents claim to be connected to the online environment, regardless of the device used at that moment. Similarly, "time spent following influencers" refers to the average number of hours per day dedicated to interacting with online influencers by viewing the content they generate. The variable “number of influencers followed” was operationalized to quantitatively assess modern consumer’s relationships with online influencers, measured by the number of influencer-held accounts followed by each respondent. Next, for the variable "online activities," we track the set of digital behaviours that respondents to this study consistently perform online, which includes the following list of activities: checking social media accounts, writing messages, audio contact, video contact, payments/transfers, online shopping, online bookings, searching for information, watching movies, music, online games, checking the weather, checking the time, watching tutorials/courses. In fact, for "offline activities" we mention non-digital activities, namely those interactions or tasks that the respondent performs without depending in any way on the online environment or smart devices. Therefore, the list of these activities becomes: offline socialising, offline shopping, offline recreational activities, watching movies on TV, offline household activities, time with kids, taking courses.

4. Results and Discussion

This section is representative of the results of research conducted based on data collected from smart consumers of the 21st century who investigate digital consumption behaviour. This corresponds to the first research objective (O1), which addresses Hypothesis 1 by examining the potential positive correlation between the quantity of influencers followed and the respondents’ total online duration. In this regard, Figure 2 provides a graphical representation of all the domains of these influencers.

Thus, certain themes stand out, implicitly revealing the media consumption preferences of our target audience, namely Travel (with 33 mentions), Finance (also with 33 mentions), as well as Personal Development and Cooking, with 32 and 31 mentions, respectively. These indicate that users' interests are oriented towards education, inspiration, and lifestyle, which corresponds to the individual's need to follow relaxing and motivational content (Croes & Bartels, 2021), but also to spend time on websites related to various information and leisure (Lut et al., 2021). In addition, this content can stimulate constant exposure, as these are areas that require continuous interaction, and thus we can mention that modern users frequently consume digital content. In addition, there are 24 consumers who selected that they do not follow influencers at all, as they are not interested in any area.

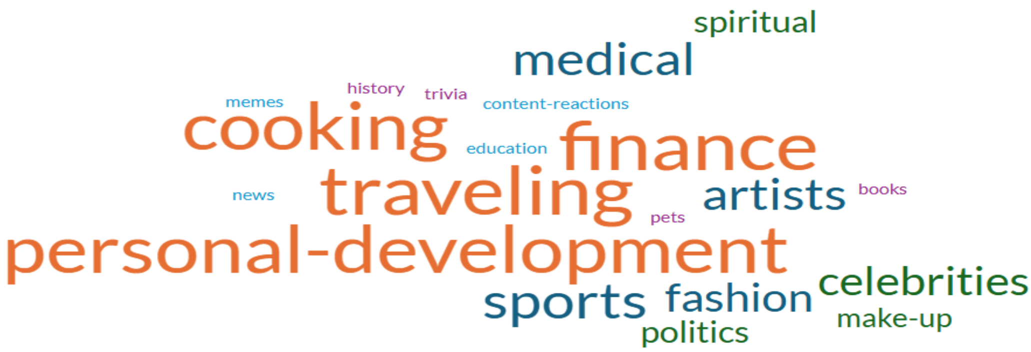

Figure 2. All areas of influencers that the respondents are following online (Source: own processing using https://www.freewordcloudgenerator.com/)

Before starting our analyses, an internal consistency reliability test was performed on all 22 items that were used in the performed statistical tests. The results of the test show that the 22-item scale was confirmed. The measure demonstrated an excellent level of reliability, showing Cronbach's Alpha of alpha = 0.896, as also seen from Table 2. This value suggests that the items are highly consistent and reliably measure a shared latent construct. Although the overall scale exhibited strong internal consistency, an initial examination of the inter-item correlation matrix indicated distinct groupings among the items (specifically between online and offline activities). Consequently, to ensure that subsequent statistical models were based on valid and unidimensional constructs, factor analysis was conducted to formally identify and establish the appropriate subscales .

Table 2. Scale Reliability Analysis

Reliability indicator	**Value**	**95% CI**	**F (df1, df2)**	**Sig.**
Cronbach's Alpha	0.896	—	—	—
Cronbach's Alpha (standardised items)	0.918	—	—	—
Number of items	22	—	—	—
ICC (single measures)	0.220	[0.176, 0.273]	9.576 (194, 4074)	$p < 0.001$
ICC (average measures)	0.861	[0.824, 0.892]	9.576 (194, 4074)	$p < 0.001$

Model specification: Two-way mixed-effects model, absolute agreement, random effects for respondents and fixed effects for measures.
**** Reliability is significant at the 0.001 level.*

Also, after analysing our dataset, we concluded that the first hypothesis is accepted and, moreover, is statistically significant. Specifically, the observed p-value was below the conventional significance threshold of 0.05, as shown in Table 3. This lays the foundation for the idea that users who follow more influencers tend to consume more online content in general, frequently viewing posted information and participating in digital activities. In fact, the literature supports the fact that as the digital environment evolves, consumption itself will increase, with behaviours changing in line with digitisation (Alzubi, 2023). Although there is a positive association between the two variables chosen, namely time spent online and the number of influencers followed, the link is not very strong, with a relatively modest Pearson coefficient of $r = .219$. Effect sizes were reported as Pearson's r for correlation analyses and as standardised beta coefficients and R^2 values for regression models.

Table 3. Correlation Analysis

Variables	**Time Spent Connected**	**Influencers Followed**
Time Spent Connected	*1.000*	*.219***
Influencers Followed	*.219***	*1.000*
Significance (p)	—	*.002*
Sample size	*N = 195*	—

Next, the analysis examines whether time spent following influencers and time spent online significantly predict the number of influencers followed (H2).

Thus, Table 4 presents the main outputs of the multiple regression analysis, which are discussed in detail below. Respectively, from the first table of the multiple regression, entitled Model Summary, we can see that Durbin-Watson records a value of 1.947, which supports the fact that there are no autocorrelation problems between our data for the respective model, thus confirming the validity of the regression model.

Moreover, the fact that $R = .337$ indicates a moderate relationship between predictors, and the value of R^2, namely 0.114, suggests that the model explains 11.4% of the variance in why people follow a different number of influencers online. Although the percentage is not very high, it still indicates an effect that must be taken into account in the given context.

Moving on to the second table we note that the value of p is less than 0.001, which explains that the model is statistically significant. The coefficients table shows that for each unit increase in time spent watching influencers, respondents follow an additional 0.207 influencers.Therefore, this is explained as being the strongest predictor since it has the highest beta value. Regarding the connected time predictor, we can say that for each unit increase in connection time, people follow 0.167 more influencers, thus marking the significant, but slightly weaker effect it has. In addition, if the influencer has a high number of followers, the user perceives them as popular and is more easily convinced to consume their content, implicitly browsing through their online posts (De Veirman, Cauberghe, & Hudders, 2017).

Table 4. Multiple Regression Analysis

Predictor	**B**	**Std. Error**	**Beta**	**t**	**p**	**95% CI for B**
Constant	*3.603****	*0.490*	—	*7.355*	*< .001*	*[2.637, 4.569]*
Time watching influencers	*0.207****	*0.055*	*0.257*	*3.781*	*< .001*	*[0.099, 0.316]*
Time connected	*0.167****	*0.050*	*0.228*	*3.355*	*.001*	*[0.069, 0.265]*

Model fit: $R = .337$, $R^2 = .114$, Adjusted $R^2 = .105$, $F(2, 192) = 12.32$, $p < .001$, Std. Error of the estimate = 3.734, Durbin–Watson = 1.95.
*** Correlation is significant at the 0.01 level.*

In other words, both types of time use manage to predict influencer following behaviour, but there are a multitude of unexplained variations in the actual reason why users choose to follow a different number of influencers. Therefore, regarding the second hypothesis, there is a significant and positive relationship between time spent online, browsing content posted by influencers, and the actual number of influencers followed. In fact, the stronger the connection between a consumer and an influencer, the more likely the content consumer is to interact with what the influencer promotes or posts (Ki et al., 2020).

For the second objective, we note whether there are differences between generations in terms of the time consumers spend online.

Preliminary analyses indicated that the mean time spent online differed significantly from zero ($p < 0.001$). Time spent online has a very high t-value of 19,470, with a mean of 7,508 units, indicating that participants spend a substantial amount of time online, with 95% confidence that the true population mean lies between 6.75 and 8.27.

For the generation variable, the extremely high t-value ($t = 44.35$) and the mean score of 1.57 (95% CI: 1.50–1.64) indicate that the sample distribution differs significantly from the zero-reference value used in the one-sample t-test (Table 5). Overall, these results confirm that both variables have significant values, different from zero, in the population, providing a basis for further statistical analysis. The literature also supports the fact that there are small differences between 21st century digital consumers, with Gen Z and millennials at the top of the online interaction rankings (Arbanas et al., 2024). Cohen's d was calculated for both t-tests, yielding a value of $d = 1.57$ for the gender comparison. Cohen's d value of 1.57 falls firmly within the "very large" effect size category. This value indicates that the difference between the two groups is approximately 1.57 standard deviations.

For the t-test regarding generation, the results were Cohen's $d = 1.55$. The analysis revealed an exceptionally large effect size for the primary comparison, with Cohen's d calculated at 1.55. According to conventional guidelines, an effect size exceeding 0.8 is considered large, placing this finding firmly within the "very large" category (Becker, 2000). This magnitude of effect signifies that the difference between the two groups (or the impact of the intervention) is approximately 1.55 standard deviations. In practical terms, this translates to a high degree of separation between the distributions, indicating that the mean score of one group is substantially and meaningfully higher than the other. The calculations have been computed using Peter statistic website, since the version of SPSS we own doesn't have this formula included (Peter Statistics).

Table 5. One-Sample t-Test Results Generation and Gender

Variable	t-statistics	df	p (2-tailed)	Mean Difference	95% Confidence Interval
Time Spent Connected	*19.470*	*194*	*< .001*	*7.508*	*[6.75, 8.27]*
Generation	*44.350*	*194*	*< .001*	*1.574*	*[1.50, 1.64]*
Gender	*41.714*	*194*	*< .001*	*1.497*	*[1.43, 1.57]*

Test value = 0

Regarding gender differences and consumer time spent online, we present Table 5. Therefore, the results of the one-sample t-test show that both variables mentioned above are significantly different from the zero-reference value, where $p < 0.001$.

In other words, for the time spent online, we present the value t as = 19.470, which is very high, with an average of 7.508 units. This indicates that the participants in the sample spend a substantial amount of time connected to the online environment, with a confidence level of 95%, and the actual average for the population is between 6.75 and 8.27. This marks the high level of connectivity and navigation in virtual environments specific to the younger and middle generations, namely Gen Z and millennials (Lut et al., 2021), who are accustomed to modern technologies and digital approaches (Gbadeyan & Bayrakktar, 2000; Prensky, 2001).

Regarding the gender variable of the respondents, the extremely high t-value, namely 41.714, together with the mean of 1.497 (confidence interval recorded between 1.43–1.57) suggests that the sample has a slight female majority, assuming the typical coding of 1 = male and 2 = female. This is also highlighted by a study conducted by Anderson, Faverio, and Gottfried (2023), where young women were more likely to spend more time on social media than young men. However, the data suggest that both variables have significant values, i.e., different from zero, in the population, thus providing a basis for further statistical analysis.

The third objective discusses the activities recorded by consumers, which are divided into two representative factors, the online environment and the offline environment, and whether there are significant correlations between them. Thus, according to Annex 7, there is a clear separation between offline and online activities, with each group being highly correlated internally. Moreover, offline activities, such as socialising, shopping, recreational activities, or household chores, are notable for their strong correlations, where $r > .70$. In fact, the recorded data suggests a behavioural profile oriented towards the offline ecosystem.

Similarly, activities carried out in the online environment, such as social media, gaming, watching influencers, or online courses, are intensely correlated ($r > .80$) and indicate a pronounced digital profile. In particular, when discussing the two types of modern consumer behaviour, we emphasise the correlations between these offline and online activities as moderate but significant, with r ranging between .20 and .40. Therefore, it is suggested that individuals tend to divide their time between the two spheres (Panagiotou, Lazou, & Baliou, 2022), with some areas of overlap, such as education, for example, with studying being done both offline and online. Respectively, once they join online social networks, users spend more time online, but also engage in offline physical activities (Althoff, Jindal, & Leskovec, 2017).

Table 6 illustrates the Kaiser-Meyer-Olkin measure as equal to 0.927 and indicates an excellent sampling adequacy, which is well above the minimum recommended threshold of 0.60. Thus, it is suggested that the data are very suitable for factor analysis. Furthermore, the Bartlett sphericity test is highly significant ($\chi^2 = 3687.945$ and $p < 0.001$), also confirming that the variables are sufficiently correlated to justify factor analysis. Once the robustness of the model has been established, we move on to data analysis and successfully extract two components with eigenvalues greater than 1.

Table 6. KMO and Bartlett's Test for Factorability

Test	**Value**
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	*.927*
Bartlett's Test of Sphericity	
Approx. Chi-Square	*3687.945*
df	*105*
Sig.	*< .001*

KMO = .927 indicates excellent sampling adequacy; Bartlett's test is highly significant, supporting factorability of the data.

Therefore, Component 1 has an eigenvalue of 8.537 and explains 56.9% of the total variance, while Component 2 has an eigenvalue of 3.514 and explains 23.4% of the variance. Together, these two components represent 80.3% of the total variance of the recorded data, which is considered excellent, with 60–70% often considered acceptable. After rotation, we find in Figure 8 the variance distributed more evenly between the two factors, Component 1 explaining 46.0% and Component 2 explaining 34.3% of the variance.

In other words, this redistribution suggests that the rotation has created a cleaner and more interpretable factor structure for our study. Thus, the remaining 13 components have eigenvalues below 1 and individually explain very little variance (ranging from 0.4% to 4.6%), indicating that they represent mostly random noise rather than significant factors.

The analysis reveals a distinct two-factor solution that clearly separates online activities from those performed traditionally (offline). Thus, the rotation created an excellent, simple structure, in which each variable loads heavily on one factor and minimally on the other, indicating clear discriminant validity.

In Component 1, represented by online activities (46.0% of variance), all digital and Internet-based activities stand out, with exceptionally high values ranging from 0.848 to 0.941. Respectively, the most representative are "following influencers" (0.941), "checking/sending emails" (0.936), "searching for information online" (0.927), "gaming" (0.927), and "online educational activities" (0.920). In particular, all these digital behaviours have strong values above 0.84, with minimum cross-values on Component 2 (all below 0.25). Essentially, it is demonstrated that these online behaviours form a coherent and unified construct.

The second component is based on offline activities (34.3% of variance). This factor represents traditional, non-digital activities, with high values ranging from 0.695 to 0.903. The strongest values are for "offline household activities" (0.903), "offline recreational activities" (0.900), and "offline shopping" (0.883). In this way, offline activities rely substantially on this factor (above 0.69), with minimal cross-values on Component 1 (all below 0.28), thus confirming the grouping as a distinct dimension of offline behaviours.

Therefore, the results of this analysis, shown in Table 7 and Table 8, suggest that people's time use patterns are fundamentally organised around the online/offline distinction. People who spend more time with one type of online activity tend to engage in other online activities as well, and the same pattern holds true for traditionally performed activities (Althoff, Jindal, & Leskovec, 2017; Chen, 2020; Lut et al., 2021). In other words, there are two relatively independent behavioural dimensions in how people allocate their time, supporting a digital divide in preferences for activities and lifestyle patterns.

Table 7. Principal Component Analysis Results

Component	Initial Eigenvalues (Total)	% of Variance	Cumulative %	Extraction Sums of Squared Loadings (Total)	% of Variance	Cumulative %	Rotation Sums of Squared Loadings (Total)	% of Variance	Cumulative
1	*8.537*	*56.913%*	*56.913%*	*8.537*	*56.913%*	*56.913%*	*6.905*	*46.033%*	*46.033%*
2	*3.514*	*23.426%*	*80.339%*	*3.514*	*23.426%*	*80.339%*	*5.146*	*34.306%*	*80.339%*
3	*.690*	*4.600%*	*84.940%*	—	—	—	—	—	—
4	*.434*	*2.892%*	*87.832%*	—	—	—	—	—	—
5	*.362*	*2.411%*	*90.243%*	—	—	—	—	—	—
6	*.307*	*2.049%*	*92.292%*	—	—	—	—	—	—
7	*.250*	*1.665%*	*93.957%*	—	—	—	—	—	—
8	*.197*	*1.314%*	*95.270%*	—	—	—	—	—	—
9	*.168*	*1.120%*	*96.391%*	—	—	—	—	—	—
10	*.151*	*1.003%*	*97.394%*	—	—	—	—	—	—
11	*.112*	*0.747%*	*98.141%*	—	—	—	—	—	—
12	*.089*	*0.595%*	*98.736%*	—	—	—	—	—	—
13	*.071*	*0.475%*	*99.211%*	—	—	—	—	—	—
14	*.064*	*0.426%*	*99.638%*	—	—	—	—	—	—
15	*.054*	*0.362%*	*100.000%*	—	—	—	—	—	—

Extraction method: Principal Component Analysis.

Table 8. Rotated Component Matrix - Principal Component Analysis

Variable	**Component 1 (Online Activities)**	**Component 2 (Offline Activities)**
Time spent socializing offline	*.050*	*.800*
Time spent shopping offline	*.217*	*.883*
Time spent on recreational activities offline	*.118*	*.900*
Time spent watching movies on TV	*.180*	*.845*
Time spent on offline household activities	*.130*	*.903*
Time spent offline with kids	*.256*	*.695*
Time spent offline on courses	*.274*	*.788*
Social media (browsing, communication)	*.848*	*.171*
Time online while working	*.891*	*.105*
Time searching information online	*.927*	*.220*
Time spent on recreational activities online	*.902*	*.187*
Time spent on educational activities online	*.920*	*.233*
Time spent watching influencers	*.941*	*.198*
Time spent gaming	*.927*	*.177*
Time spent verifying and sending e-mails	*.936*	*.188*

Rotation method: Varimax with Kaiser normalization; loadings ≥ .70 are highlighted

Notes:

- *Extraction method: Principal Component Analysis*
- *Rotation method: Varimax with Kaiser normalisation*
- *Rotation converged in 3 iterations*
- *Loadings ≥ .70 indicate a strong association with the factor*

Next, the fourth research objective examines generational differences in the use of smart devices accessed via smartphones; accordingly, Figure 3 illustrates the smart objects used by respondents and their frequency of use.

Therefore, data analysis shows that the most used device, and we can say that for both generations, is the smart TV, with a frequency among Generation Y (n = 45) and Generation Z (n = 63). In other words, regardless of the age of the respondents, they tend to integrate into their lives a form of entertainment that is easily accessible and connected to multiple types of content, such as streaming, TV games, or music (Twenge, Martin, & Spitzberg, 2019; Widener et al., 2025). However, young people are more likely to spend more time navigating the menus of a smart TV, consuming more media content (Alzubi, 2023).

Also, if we were to analyse only the smart objects used by Generation Y, we would see that the most common devices are those associated with creating comfort in the home, such as surveillance cameras (n = 29), air conditioning (n = 24), vacuum cleaners (n = 24), and heating systems (n = 20). Thus, this generation is distinguished by a high degree of desired efficiency with the help of digitally connected objects, emphasising their desire for stability, convenience (Alzubi, 2023), and domestic control (Bocxlaer, 2024). Moreover, younger generations tend to invest in smart home technologies (Kolny, 2022). Compared to this instrumental function highlighted by Generation Y, Generation Z is oriented towards devices that enhance entertainment in everyday life, such as smart TVs and even cars (n = 16).

Furthermore, there are items that have not been mentioned so far, such as Play Station (PS4), headphones, or voice assistants, which portray Generation Z as familiar with modern technologies since they were born into the whirlwind of these digital ecosystems (Panagiotou, Lazou, & Baliou, 2022). In addition, this generation is also notable for its willingness to integrate experimental devices, out of curiosity or enthusiasm for the possibility, with higher values recorded for door and window control (n = 7), but also for the oven (n = 6) and blinds (n = 4).

Overall, generational differences confirm existing trends in the literature, namely that Generation Y is predisposed to use smart objects pragmatically, choosing comfort and creating a practical space in the home, while Generation Z wants connectivity and entertainment (Panagiotou, Lazou, & Baliou, 2022). Thus, young people, already considered natives of modern technologies, tend to want more interaction with digital ecosystems and to experience their diversity. In fact, data confirms that the number of individuals who embrace an interconnected home has been growing steadily in recent years (Eurostat, 2023).

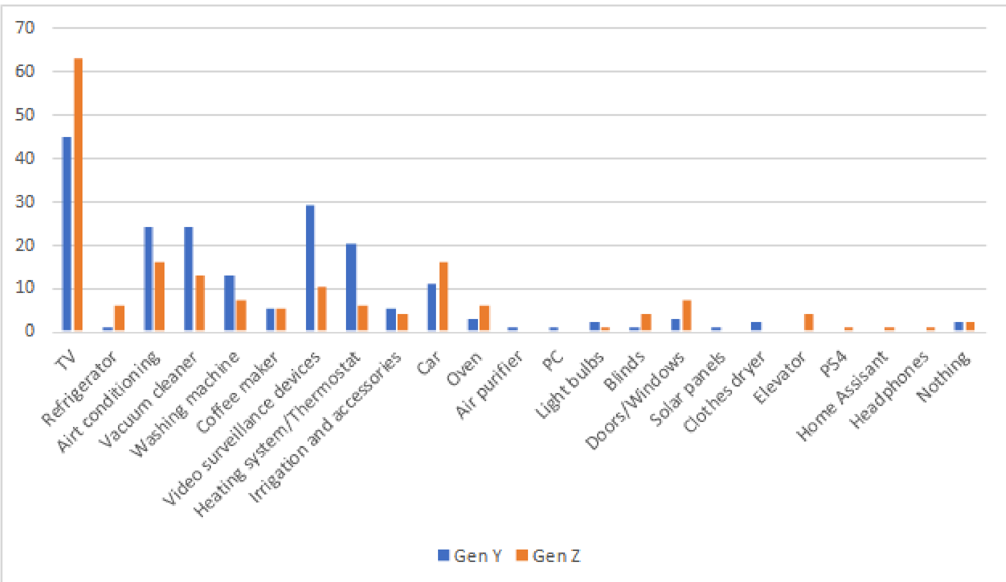

Figure 3. The most used devices by phone by generation. (Source: own processing)

The way respondents allocate their time to offline activities is an important trajectory for the next objective and marks the hybrid behaviour of digital consumers, where virtual and traditional experiences are effectively combined. Table 9 shows that respondents allocated a significant number of hours to certain offline activities, such as socialising, recreational activities, household activities, and watching cable TV.

Table 9. The offline activities most representative of the target population

Offline activities Total hours	Hours spent	'I do not do these activities'
Socialising	731	5
Recreational activities (e.g. reading, hobbies, gardening, etc.)	556	6
Household activities (e.g. cooking, cleaning, yard work)	535	7
Watching movies on cable TV	523	12
In person courses/qualifications	451	34
Shopping	366	10
Spending time with children	303	81

Accordingly, socialising emerges as the most significant offline activity for modern users, accounting for 731 hours spent in face-to-face interactions. Despite the growing presence of digital technologies in everyday life, it is shown that certain offline behaviours continue to play a central role in the consumer's well-being and satisfaction. There is also a category of consumers who do not engage in one or more of the activities represented in the table above, namely time spent with children and courses or qualifications, which are at the bottom of the list. One explanation could be that our respondents, being part of younger generations, do not yet prioritise time for children, focusing instead on other experiences that develop them, either online or offline.

In examining objective 6, we focus on how smart devices, namely those that are part of the Internet of Things, influence consumers' online behaviours. Thus, in the context of the digitisation of everyday life, Table 10 shows a collection of these devices and, implicitly, the high frequency with which respondents use them in their daily activities.

Table 10. Associations between smart devices and consumers' online activities

Digital activities Smart devices	Smartphone	Tablet	Laptop	Desktop	Smart TV	Smart Watc	No devic
Checking social media accounts	***185***	14	36	11	2	4	2
Writing messages	***180***	9	41	10	2	4	0
Audio contact	***166***	11	41	9	17	5	1
Video contact	***161***	15	44	15	20	4	5
Payments/Transfers	***173***	8	36	11	4	1	2
Online shopping	***149***	9	***71***	17	2	5	2
Online bookings	***146***	5	64	18	3	2	6
Searching for information	***149***	12	***92***	14	5	2	1
Watching movies	61	13	***93***	15	***73***	5	1
Music	***139***	16	***76***	17	27	3	2
Online games	***90***	5	57	20	4	3	49
Checking the weather	***171***	11	23	7	2	11	4
Checking the time	***180***	9	26	9	6	25	1
Watching tutorials/courses	***117***	18	***93***	17	9	0	9
Total	2067	155	793	190	176	74	85

Here, we find everything from phones and tablets to televisions and smart watches, all of these smart objects being associated with a series of recurring digital activities for a modern consumer, such as writing messages, searching for information, listening to music, or even checking the weather (Eurostat, 2023). Therefore, identifying these associations is significant for our study as it helps us understand the extent to which the Internet of Things shapes the experience of smart consumers, marking a strong relationship between the 21st century user and digital consumption.

Most of the time, there is a tendency to perform as many activities as possible using a smartphone (Anderson, Faverio & Gottfried, 2023; Bocxlaer, 2024), but there are also certain behaviours where the phone is not necessarily the main device of choice. In this regard, activities such as "watching movies" or "searching for information" stand out because, although there are uses for the phone, the visual comfort of the laptop or smart TV comes into play. Thus, high values (highlighted in *italic red* in the table) are also recorded for other smart objects that offer different advantages in terms of screen size or keyboard availability.

Also, the level of smartphone usage is undoubtedly the highest, ranking first and far ahead of other smart devices. Users do not only use their phones to check social media and chat with various people, but also to make payments, purchase products, or book trips. Therefore, smartphones are not only perceived as a means of communication, but also as a way to organise consumer resources, coordinating their lives with the help of a multifunctional smart device (Al-Zoubi, 2024).

Table 11 shows the cumulative frequency of all digital interactions and thus marks the smartphone as the core device of the modern consumer's digital ecosystem, as confirmed by a July 2024 study, where 95.9% of the population surveyed uses a smartphone for various Internet-related activities (GWI, 2024).

Table 11. Descending list of smart device frequency according to digital activities

Smart Device	Total frequency
Phone	2067
Laptop	793
Desktop	190
Smart TV	176
Tablet	155
No device	85
Smartwatch	74

In particular, the data recorded indicates that most digital activities are carried out via the phone, a statement also confirmed by Panagiotou, Lazou, & Baliou (2022). In addition, the values found were interpreted as the highest for almost all consumer behaviours, emphasising, in accordance with the literature, the central role it plays in the personal network of smart devices, being a versatile tool in consumers' daily lives (Al-Zoubi, 2024).

4. Conclusion

The data analysed in this study illustrate the digital behaviour of the smart consumer in Romania, with a particular focus on the relationship between time spent online, social media interaction, and the management of daily activities through smart devices. Collectively, there are various positive and statistically significant correlations that explain the online interactions of modern users and, more than that, highlight the impact of constant exposure to the digital environment. Therefore, the more a consumer consumes content generated by influencers, the stronger their involvement in the virtual ecosystem becomes, increasing the individual's connectivity with the online environment. In fact, digital behaviour is significant for Generation Y and Generation Z, with the actual amount of time spent browsing being high, regardless of whether the dynamics of interactions may fluctuate depending on age or gender.

At the same time,there are also certain negative effects that can occur when internet use and digital browsing are taken to extremes, namely, certain states of anxiety, discomfort, and physical fatigue due to lack of sleep or the fact that the body remains motionless for a long period of time. In fact, various studies associate time spent online with depression, especially if the consumer interacts with the online environment for more than two hours a day (Zhu et al., 2025). In addition, once they have become accustomed to this behaviour, it is difficult for them to limit their access to screens and the internet (Arbanas et al., 2024) and, moreover, the total lack of internet accessibility becomes a real discomfort for them (Milková, Kaliba, & Ambrožová, 2022).

Accordingly, two distinct and representative dimensions of modern daily life have been identified, namely online and offline. Thus, there are two different behaviours, each strongly influenced by the environment in which it occurs, but interrelated. In particular, a hybrid lifestyle has been identified, in which the smart consumer oscillates between a comfortable digital life that they can control efficiently and a traditional life where they spend time socialising and recharging their "batteries" through recreational activities. We also noticed that certain smart objects are preferred depending on the generations analysed, namely, Generation Y tends towards devices that make life easier and are efficient for the home (air conditioning, vacuum cleaner, thermostat), while Generation Z is oriented towards entertainment and connectivity with the digital world (smart TV, voice assistants, PS4). In addition, for every smart consumer, we can say that digital activities are mainly carried out via smartphones. Moreover, these devices, which are part of the Internet of Things, manage to create a balance between the individual, their daily activities, and online interactions.

Therefore, the study manages to project the profile of a smart consumer who is oriented towards functionality, connectivity, and balance between online and traditional life. Thus, the identified social influences, consumer activities, and the devices they use contribute to the literature on modern digital behaviours and smart objects. In other words, the study provides a better understanding of the relationship between technology, time, and the 21st century consumer. In terms of practical recommendations that can be drawn from this study, we emphasise the relevance of the results for the field of technological design, but also for marketing, making it possible to capitalise on the decision-making factors of modern users. Essentially, we are discussing the adaptability of digital interfaces to the usage styles of the aforementioned generations and, more than that, the development of marketing strategies that respond to the needs and preferences of smart consumers. Thus, integrating the implications according to the level of involvement in the online environment of smart consumers can be a valuable guide in developing solutions focused on modern users.

5. Recommendations and Limitations

In terms of areas for improvement, a key limitation of the study is the somewhat unrepresentative nature of the surveyed sample. In other words, there is a variety of individuals from across the country who responded to our set of questions, but there is a relative difference in their ages, with the data set representative of individuals belonging to Generation Z being larger than that of Generation Y.

Consequently, we emphasise that the sample distribution is not entirely uniform, which may affect the conclusions of the study to some extent, since they cannot be generalised to larger populations. Additionally, we must also bear in mind the representative limit for the use of self-reported data, since there may be subjective responses, perhaps even overestimated or underestimated, depending on the individual perception of each respondent.

With regard to the variables included in our study, we acknowledge that the entire range of dimensions associated with Internet of Things ecosystems has not been included and, we affirm that there is still an opportunity to conduct a new study in which, in addition to all the components mentioned in this study, those that we excluded in the methodology section could also be included.

In the same manner, a future direction would be to complete the sample with an equal number of respondents from the two generations and perhaps even extend it to Generation Alpha in order to observe significant differences in digital behaviours based on the ages of the respondents.

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