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Spare time use: profiles of Italian Millennials (beyond the media hype)

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Abstract

This paper focuses on a particular population segment, that of Millennials, which has attracted much attention over recent years. Beyond the media hype, little is known about the habits of this generation towards spare time use. The present study builds on a previous work devoted to detect the different ways Italian Millennials interact with spare time, and aims at identifying profiles of Millennials branded with profile-specific time use habits and styles. In so doing, we (i) account for the multidimensional nature of time use attitude and express it into a reduced number of distinct dimensions and (ii) identify and qualify profiles of Millennials as regards the ascertained time use dimensions. By relying on an extended Item Response Theory model applied to the Italian "Multipurpose survey on households", our main findings reveal that the way Millennials use spare time and interact with technology is much more complex, varied and multifaceted than what claimed by the media.

Keywords Time use · Leisure · Millennials · Italian "Multipurpose survey on households" · Latent class multidimensional IRT model

1 Introduction

Time is a complex concept that affects various aspects of people's lives. The conciliation of lifetimes, the balance between work, family life, social activities and personal needs is closely related to people's well-being. In this direction, in the last decade or so, eminent studies have indicated subjective well-being linked to lifetimes as one of the key dimensions of quality of life (Stiglitz et al. 2010).

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Millennials (also called Generation Y) is a generation of people known to handle new media far more comprehensively than older generations. This is true in Italy, which is the specific context of the present work, but also at the European level (ISTAT 2019). However, unexpectedly, little empirical research exists on the ways Millennials interact with various activities, including the new media, during their time. Early studies on the impact of information technology (IT) on society at large (Kraut et al. 1998; Nie and Erbring 2000) suggest that it has a negative impact on social life, is associated with lower time in social capital activities (such as church attendance, social visits with relatives and friends) compared to those who spent no time on Internet, and is related to time displacement of cultural activities (such as reading, watching movies, personal arts production). Other studies (Rains et al. 2016) have suggested that interacting with Internet and social media may be detrimental to relationships and weaken relational and social ties. Further, another bulk of studies on the digital divide has long argued that less privileged Internet users are less likely to use Internet for information seeking associated with civic participation (Shah et al. 2005), such as for networking through e-mail (Boase 2008).

Perhaps because of such established studies, a widespread perception of Millennials as a generation of IT-confident young people characterised by low engagement in social capital activities and civic participation, little cultural commitment and weak social ties consolidated over time, especially in the commentary of media outlets. However, there is no scientific foundation to suggest that the outcomes found by the above cited studies at the population level can be held to exist for the younger Generation Y. What is more, a number of prominent studies provide complementary viewpoints compared to the studies mentioned above. For instance, there are indications that IT use and social media do strengthen relational closeness (Burke and Kraut 2014) and are associated with having a larger number of core social ties (Hampton et al. 2011; Hampton 2016). Robinson and Kestnbaum (1999) further showed that new technology users are more likely to engage in cultural and leisure activities, using their time particularly for the printed medium of reading, for watching a movie, and for personal arts production. In a study carried out on the General Social Survey and the American Time-Use Survey, Robinson and Martin (2009) also demonstrated that Internet use was not consistently correlated with lower levels of socialising or other social activities. Finally, other key studies on the digital divide—such as that of Hampton (2010)— do offer evidence that Internet use tends to reduce inequalities in social and civic participation by serving as a contextual leveller between advantaged and disadvantaged communities, through the reduction of the transaction costs of local communication. In so doing, these latest studies provide evidence of opposite outcomes compared to the previous established literature on the digital divide.

The purpose of this article is an in-depth study of personality profiles of Italian Millennials on account of their attitudes towards spare time use and, within it, media use. To this aim, we characterise the distinctive activity types of Millennials and determine whether qualitative differences exist among them based on the nature of time and media use. Beyond widespread perceptions, little is known about Millennials (New Zealand Management 2007; Schofield and Honoré 2009).

Furthermore, past research on Generation Y behaviour tended to center on one dimension at a time (i.e., Internet usage) and adopted an oversimplifying approach—for instance, by reporting the total number of people using Internet or how frequently people use new media (Losh 2003)—ignoring very different patterns of time use (Brandtzæg 2010) and homogenising very diverse activities (i.e., Internet use for chatting, Internet use for downloading newspapers, etc.), then overlooking crucial qualitative differences within time and Internet usage.

Besides, despite in more recent years the literature has started to pay more attention to the different ways individuals use time and interact with the new media (Ortega Egea et al. 2007; Horrigan 2007; Brandtzaeg and Heim 2011), there is still a lack of studies aiming at profiling time user types by concurrently accounting for the qualitatively different dimensions of time and media use behaviour. In fact, the existing body of literature tends to show a mutual exclusive use of two techniques and two objectives: studies tend to focus either on factor analysis alone to identify dimensions of time use and characterise the nature of time use behaviour (Heim et al. 2007; Johnson and Kulpa 2007), or alternatively on cluster analysis to identify distinctive time user types (e.g., see Ortega Egea et al. 2007; Horrigan 2007; Li et al. 2007). Only few exceptions, though not specifically targeted at studying Millennials, try to combine the two instances—see at this regard the work of Brandtzæg (2010)—to the aim of qualifying profiles of units on account of time use dimensions.

To our knowledge, no study (neither in Italy nor in other countries) focuses on disentangling Millennials' behaviour as regards their spare time usage, by taking into account the multidimensional nature of this phenomenon. Specifically, some works on this population segment focus only on particular aspects of Millennials' lifetime, such as media use (Botterill et al. 2015), use of technology at work (Kim 2018), impact of new technology (Vilhelmson et al. 2018). In Italy as well, recent studies on Generation Y pay attention only to specific themes, such as, among others, connection between social networking and social inclusion (Introini and Pasqualini 2019), preferences for wine consumption and purchasing behaviours (Gallenti et al. 2019; Iazzi et al. 2020; Nassivera et al. 2020), preferences about means of transport (Nosi et al. 2017; Magnani et al. 2018), competencies needed for a leadership (D'Amato and Macchi 2019). Other studies concentrate on Millennials as a whole—i.e., to the aim of comparing time use styles of both Millennials versus non Millennials (Freeman 2019) and younger versus older Millennials (Garikapati et al. 2016)—and thus provide a general portrait.

In the present paper, we aim at (i) capturing the multidimensional nature of time and Internet use of Millennials by expressing it into a reduced number of distinct sub-dimensions and (ii) identifying and qualifying profiles of Millennials as regards the identified time use sub-dimensions. Finally, given the contrasting outcomes of the existing literature on the digital divide, we portray the identified profiles on account of a number of covariates describing Generation Y, that is, gender, geographic residence, education level and professional status.

To these purposes, we use data made available in 2012 by the "Multipurpose survey on households: aspects of daily life" (ISTAT 2016). Further, we rely on an extended Item Response Theory (IRT) model, that is, the latent class

multidimensional IRT model (Bartolucci 2007). In general, and as it will be further clarified in the next section, IRT models are particularly useful methodological tools any time the data have a latent structure, as in our case, where attitudes towards time can be seen as a latent, not-directly observable variable. Specifically, the model we apply has two main differences with respect to classic IRT models: (i) the latent structure in the data is assumed to be multidimensional and (ii) it is based on latent variables with a discrete distribution, meaning that the population under study is made up by a finite number of classes, with subjects in the same class having the same level of the latent variable (i.e., time and Internet use, in our case study). The chosen model is therefore a powerful instrument as it allows us to concurrently reach the two above mentioned key objectives, that is, clustering (or grouping) units into classes or profiles, by retaining the multidimensional facet of time use.

The article is organised as follows. In Sect. 2 we extend the discussion on the usefulness of the above mentioned model to the aim of profiling Millennials and provide details on the statistical formulation of the model. In Sect. 3 we apply the model to the Multipurpose survey on households (used for building our final dataset); to this aim, we first describe the data at hand and subsequently report the main outcomes of our study. Finally, Sect. 4 draws the main conclusions from the study and proposes some future developments.

2 Profiling Millennials: potentials of extended IRT models

Attitude towards time and Internet use is a multidimensional and latent variable (Gnaldi and Del Sarto 2018). It is latent as it cannot be observed directly in the data, and can only be inferred from overt behaviours, that is, the responses to the items of a questionnaire survey on time use. It is multidimensional as various dimensions contribute to form the overall construct. In fact, people can spend free time for socialising, having rest, volunteering, etc., each, in turn, made of many single activities: for instance, having rest may imply sleeping, listening to the radio, chatting with friends, and so on.

Past studies on time use have implicitly (and sometimes explicitly) recognised the complexity and multidimensionality inherent time use attitude. In fact, virtually all of them have used techniques of data complexity reduction, such as factor and principal component analysis on the one hand, and cluster analysis on the other—see for reference Hotelling (1933), Tryon (1958), Harman (1976) and McDonald (1985)—to select the number and nature of the dimensions composing time use, and to identify profiles of individuals on account of their attitude towards time. The former methods are best suited for dimensionality assessment and are therefore useful for studying the latent dimensionality structure of a complex phenomenon. The latter is mostly used for classification purposes, that is, to classify individual units into groups with respect to certain characteristics.

However, no study, to our knowledge, has relied on models developed in the IRT framework, which, as anticipated in the previous section, are particularly suited for the study context at issue, as they assume that the associations between individuals' responses are accounted for by a latent trait, which, in our context, is the attitude

towards time use. Traditional IRT models consider a unique latent trait (i.e., with a single dimension), represented by a latent variable with a continuous distribution. Multidimensional IRT models (Reckase 2009) extend the classic IRT models, by assuming that the underlying latent trait may be represented by several and potentially related dimensions (i.e., more latent traits). Despite this extension allows us to take into account the multidimensional nature of the phenomenon under study, the continuous distribution, assumed for the latent variables underlying the multiple latent traits, is not suitable for clustering the statistical units.

For these reasons, a very appropriate model for our purposes is that introduced by Bartolucci (2007), which connects the potentials of multidimensional IRT models with the flexibility of the latent class (LC) model (Lazarsfeld 1950; Lazarsfeld et al. 1968). Hence, on the one hand, it assumes that the responses to each item depend on some person characteristics (latent traits), and on some item features, such as the item (or variable) difficulty and discrimination level (Bartolucci et al. 2015). On the other hand, the model provides a classification of the units in groups, called latent classes, according to the underlying latent trait levels. In fact, units in the same latent class present very similar characteristics in terms of the latent traits. The following section provides technical details about the model at issue.

2.1 The latent class multidimensional IRT model

The LC model is one of the most well-known latent variables models, used to classify units of a sample in groups according to the responses to a set of categorical variables. Considering a sample made of n units, let $\boldsymbol{Y}_i = [Y_{i1}, \ldots, Y_{ir}]^\top$ denote the random vector of the responses provided by unit i to the r items of a questionnaire, with $i = 1, \ldots, n$. Each Y_{ij} is a categorical variable with l_j categories, generally labelled starting from 0 to $l_j - 1$. In the present paper, we deal with dichotomous items, hence $l_j = l = 2$ for each $j = 1, \ldots, r$, thus Y_{ij} can assume values 0 or 1 for a negative or positive response, respectively.

The LC model assumes the existence of a discrete latent variable C_i with the same distribution for each unit i. This latent variable is based on k support points. Each point has a specific prior probability, denoted by $\pi_c, c = 1, \ldots, k$ and corresponds to a latent class in the population. Furthermore, the conditional probability of success, that is, the probability that unit i, belonging to class c, provides an affirmative response to item j is:

$$\phi_{j|c} = P(Y_{ij} = 1 | C_i = c), \qquad j = 1, \ldots, r, \quad c = 1, \ldots, k. \tag{1}$$

We assume local independence between the response variables Y_{ij}, hence they are conditionally independent given the latent class. This implies that the probability of observing the response vector $\boldsymbol{y}_i = [y_{i1}, \ldots, y_{ir}]^\top$, given that unit i is in latent class c, is given by:

$$P(\mathbf{y}_i|c) = P(\mathbf{Y}_i = \mathbf{y}_i|C_i = c) = \prod_{j=1}^{r} \phi_{j|c}^{y_{ij}}(1 - \phi_{j|c})^{1-y_{ij}}.$$

Then, the manifest probability of $\mathbf{y}_i$ can be obtained as follows:

$$P(\mathbf{y}_i) = P(\mathbf{Y}_i = \mathbf{y}_i) = \sum_{c=1}^{k} P(\mathbf{y}_i|c)\pi_c.$$

It is often of interest to rely on an allocation rule, allowing to assign each sample unit to a particular latent class, given its response pattern. Such procedure is based on the posterior probability that unit i belongs to class c, given response vector $\mathbf{y}_i$. It can be obtained using the Bayes' theorem, as follows:

$$P(c|\mathbf{y}_i) = P(C_i = c|\mathbf{Y}_i = \mathbf{y}_i) = \frac{P(\mathbf{y}_i|c)\pi_c}{P(\mathbf{y}_i)}, \quad c = 1, \ldots, k. \tag{2}$$

In particular, each unit is assigned to the latent class with the largest posterior probability.

In order to connect the LC model described above with the IRT framework, the conditional probability in (1) can be written using the parametrisation of the Rasch model (Rasch 1961), which is the most well-known IRT model. The resulting model can be referred to as the LC Rasch model (Lindsay et al. 1991) and the model equation is the following:

$$\text{logit}(\phi_{j|c}) = \theta_c - \psi_j, \quad c = 1, \ldots, k, \quad j = 1, \ldots, r. \tag{3}$$

In this way, the conditional probability $\phi_{j|c}$ depends on the latent trait level for latent class c, denoted by θ_c, but also on a parameter related to the item, that is, the so-called difficulty parameter of item j, denoted by ψ_j. The main difference with respect to the traditional Rasch model concerns the hypothesis on the distribution of the underlying latent variable. In fact, in (3), θ_c is considered as the realisation of a random variable Θ having a discrete distribution with k support points, while in the original Rasch model, Θ is supposed to have a continuous distribution.

Furthermore, the model reported in (3) is also called "one-parameter logistic" (1-PL) model, since it uses only one parameter about the item and assumes constant discrimination among the questionnaire items. Such constraint can be overcome through the "two-parameter logistic" parametrisation (2-PL), with which the items can have different discrimination, denoted by λ_j. Thus, the model equation can be written as follows:

$$\text{logit}(\phi_{j|c}) = \lambda_j(\theta_c - \psi_j), \quad c = 1, \ldots, k, \quad j = 1, \ldots, r. \tag{4}$$

So far, it is assumed that the underlying latent trait—measured by a univariate latent variable Θ—is unidimensional. Such hypothesis can be considered too restrictive, since most of the phenomena often investigated using IRT models (such as an attitude, an ability, a service satisfaction, a health status, and so on) are complex and multifaceted. This means that the questionnaire items contribute to measure

different but related dimensions of the same latent concept. For this reason, let us suppose that the latent construct at issue is made of s dimensions. Now, the underlying latent variable becomes a random vector with s components, denoted by Θ. Hence, the multidimensional extension of the 2-PL model reported in (4) is the following:

$$\text{logit}(\phi_{j|c}) = \lambda_j \Big(\sum_{d=1}^{s} I_{j \in J_d} \theta_{cd} - \psi_j \Big), \quad c = 1, \ldots, k, \quad j = 1, \ldots, r, \qquad (5)$$

where $I_{j \in J_d}$ is an indicator function, equal to 1 if item j is in set J_d, that is, the set of items that contribute to measure dimension d, with $d = 1, \ldots, s$, and 0 otherwise. Furthermore, θ_{cd} is the latent trait level for unit belonging to latent class c with respect to dimension d. The model in (5) is generally referred to as the latent class multidimensional 2-PL IRT model (Bartolucci 2007; Bartolucci et al. 2012) and has a number of free parameters, denoted by m, equal to $(k-1)$ for the π_c, plus $(r-s)$ for both the λ_j and ψ_j, plus $(k \times s)$ for the θ_{cd}.

If there is not a priori information about the questionnaire dimensionality, the number of dimensions s is unknown, so as the sets J_d for $d = 1, \ldots, s$, that is, the groups of items that measure each dimension d. For this purpose, Bartolucci (2007) proposes an exploratory hierarchical clustering algorithm with the aim of estimating the latent dimensionality structure of a questionnaire. Starting from the most general model (that is, a model with r dimensions, one for each item), this procedure builds a sequence of nested models, according to (5), each one with a fewer dimension and ends with the unidimensional model ($s = 1$). Finally, among the estimated models, one for each possible value of s, from r to 1, we need to select the suitable one, hence the suitable value of s, according to statistical or other subjective criteria. For a detailed description of such algorithm, we remind to the papers of Bartolucci (2007) and Gnaldi and Del Sarto (2018).

The model reported in (5) presents all the characteristics of a multidimensional IRT model, but, at the same time, is a LC model. Specifically, two types of clustering are implemented within this model. The first concerns the latent classes, hence the statistical units in the sample and thus the population they represent. In fact, the sample units are clustered into groups according to the latent trait level, so that units in the same latent class present the same latent trait level. The second considers the items, or variables, of the questionnaire and aims at classifying them into groups, by clustering those items that contribute to measure the same dimension. Indeed, the clustering algorithm proposed by Bartolucci (2007) aims at ascertaining the actual number of dimensions of the phenomenon under study and the clusters of variables that refer to the same dimension.

Overall, the LC multidimensional IRT model in (5) allows us to build profiles (of Millennials)—as many as the number of latent classes k—referred to the phenomenon under study (spare time use habits). Such profiles characterise the latent classes in terms of the ascertained dimensions of the phenomenon at issue. The main output of such an analysis is a cross tabulation which shows the estimated latent trait levels for each class (of Millennials) and dimension (of variables). Each of these estimates can be translated in the probability for an individual grouped in

one of the latent classes to present a certain dimension of the analysed phenomenon, which in our case concerns a specific dimension of attitude towards time (Gnaldi et al. 2017).

3 The application

In this section, we show the application of the LC multidimensional IRT model described in the previous section with the aim of extracting profiles of Millennials and qualifying them in terms of free time use. Specifically, in Sect. 3.1 the data used for our purpose are described, that is, the "Multipurpose survey on households: aspect of daily life". Section 3.2 recalls the dimensions of time and media use ascertained in a previous study (Gnaldi and Del Sarto 2018) on the same sample of Generation Y people. Section 3.3 is devoted to the description of the procedure followed for clustering, or profiling, Millennials on account of their time use preferences, while Sect. 3.4 provides a detailed description of the resulting profiles. Finally, Sect. 3.5 shows a further characterisation of the ascertained profiles according to some personal features of Millennials.

3.1 The Italian "Multipurpose survey on households: aspects of daily life"

In the European context, large-scale data on time use are available in countries such as Germany and France since the 1960s. In Italy it is only with the "Multipurpose survey on households: aspects of daily life" (ISTAT 2016) that the system moved in the late 1980s to a modern one of collecting information on the resident population in private households. This survey is conducted every year by the Italian National Institute of Statistics (ISTAT) since 1993. Since its introduction, the Multipurpose survey provides empirical evidence for the essential dimensions of gender inequality, so much so that the Italian survey on the use of time—the main survey on time use—is regulated by law (no. 53 8th March 2000) to provide the Country with five-year information on the gender differences in Italian people's lifetimes.

The survey provides information on the citizens' habits and the problems they face in their every day life. Specifically, the main content areas covered by the survey relate to household and population structure, dwellings and residential areas structures, household mobility, education levels, time use, lifestyles, health conditions, domestic and non-domestic work, public and private household services.

The main reason why we chose to work with this survey is that in time use diaries—another well-known tool to extract detailed information on people's daily activities—the generic indication of PC or Internet use does not allow us to understand the type of activity undertaken. It is therefore possible that young users of IT media do not declare to read a newspaper or a book but can still do it without having made it explicit claiming to be using PC or Internet.

In this work, we consider data collected in 2012, referred to 3180 young people aged between 18 and 24. We choose to adopt a restrictive rule of units' selection by constraining our database to people aged between 18 and 24 because there is a lack of agreement in the literature on the definition of Generation Y cohort starting and

ending birth years (Tolbize 2008; Twenge et al. 2010; Pew Research Center 2015; Freeman 2019). Our choice should limit the internal heterogeneity of the cohort (in terms of employment conditions, age, gender, etc.) and control for involuntary unemployment (Stiglitz et al. 2010), which happens when individuals cannot work as much as they would like and, as a consequence, have more available leisure than they would like.

Furthermore, since the Multipurpose survey does not have a specific section devoted to free time usage, all the questions in the survey have been examined with the aim of selecting the ones concerned with the respondent's spare time use. Overall, $r = 31$ items have been retained, whose contents are reported in Table 5 in the "Appendix". A few items have only two response categories (i.e., of type "yes" or "no"), and others have more than two categories, then the response is referred to the frequency with which the respondent engages in a particular activity within a pre-specified time period. Moreover, items from 13 to 20 are coded with an affirmative response if the respondent answers "yes" to at least one of the items of the block (reported in italic face).

In their original polytomous formulation, these items make reference to the amount of time spent in each activity, that is, to the intensity of time use per activity. However, we consider a dichotomisation of them, so that all the answers different from "no" are considered affirmative. The dichotomised items can therefore be read in the same way as the presence or absence of a particular activity in the respondent's spare time (regardless of its frequency). The dichotomisation choice is justified by our interest in focusing on the popularity of time use styles in Millennials, rather than on the quantity of time allocated to each activity. In fact, several studies—see, among others, Robinson and Godbey (1997), Aguiar and Hurst (2007) and Freeman (2019)—have already paid attention to the frequency of time use, but much fewer on time use styles. Finally, missing responses are considered as negative answers, then as absence of the related activity in the respondent's spare time.

A preliminary picture of the sample at issue shows that the most frequent activities carried out are related to going out with friends (98.62%), watching television (92.14%), going to the cinema (84.15%) and using Internet to communicate (80.57%). On the other side, a very small proportion of the sample (less than 4%) attends courses or engages in private lessons in its spare time (see again Table 5 in the "Appendix").

3.2 Dimensions of Millennials' spare time use

Past research on the same data has shown that six dimensions of time and Internet use can be identified, as reported in Table 1, where the denominations for each dimension are shown, together with the IDs of the items measuring each of them. The six dimensions are ordered according to $\bar{\tilde{\phi}}$, a measure of the popularity of time use styles within Millennials. This measure of popularity is obtained from a multidimensional IRT model by taking the mean of the estimated conditional

Table 1 The six dimensions of time and Internet use of Italian Millennials—as reported in Gnaldi and Del Sarto (2018)—together with the items composing them (item content reported in Table 5 in the "Appendix"). A measure of popularity with which each dimension occurs, denoted by $\bar{\bar{\phi}}$, is also reported

Dimension	Item IDs	$\bar{\bar{\phi}}$
Socialising entertaining	9, 20, 22, 25	0.619
Technologically socialising	8, 11, 13, 16, 17, 18	0.603
Sportive	6, 7, 12, 26	0.488
Technologically engaging	1, 10, 14, 15, 19	0.420
Individually engaging	2, 4, 5, 24, 28, 29, 30, 31	0.341
Socially engaging	3, 21, 23, 27	0.211

response probability over the items that contribute to measure each dimension (Gnaldi and Del Sarto 2018).

The overall picture which emerges from this study is that socialisation, either in a non media-mediated manner or through the use of technology (as measured by dimensions "Socialising entertaining" and "Technologically socialising"), is the distinctive trait of time use activities of Italian Millennials, as already outlined by other studies (Botterill et al. 2015; Garikapati et al. 2016; Freeman 2019). In this picture, the use of technology and Internet comes into view as an important time use dimension, but subordinately to the previously mentioned dimension, as Italian Millennials devote time primarily to socialise and have fun, by sharing it with friends in a way not mediated by media.

The characterisation of time use dimensions reported in Table 1 is, however, general and concerns the whole cohort, so that the outlined dimensions refer to an "average" Generation Y person. Then, it can be of interest to deepen the analysis and focus on sub-samples, or profiles, of Millennials, and characterise them on account of the above time use dimensions, as described in the next section.

3.3 The procedure to extract profiles of Millennials

In this section, we describe the procedure followed to identify clusters of Millennials on account of their preferences as regards to time and media use. The main issue consists in selecting the number of latent classes in the model, denoted by k. Hence, several IRT models are fitted with increasing values of k, by maintaining a fixed dimensional structure (the six dimensions mentioned in Sect. 3.2). Then, according to a suitable selection procedure, the final model is identified, hence the final value of k.

To this aim, we carry out a selection process that represents a good compromise among model fitting, computational complexity and a good level of overall interpretability of the results, by using a mix of objective and subjective criteria. Specifically, model fitting is assessed through three information criteria: the Bayesian Information Criterion (BIC; Schwarz 1978), the Akaike Information Criterion index (AIC; Akaike 1973) and the Consistent Akaike Information Criterion index (CAIC; Bozdogan 1987), obtained as follows:

$$\text{BIC} = -2\hat{l} + m\log(n),$$
$$\text{AIC} = -2\hat{l} + 2m,$$
$$\text{CAIC} = -2\hat{l} + m(\log(n) + 1),$$

where $\hat{l}$ is the maximised model log-likelihood, m is the number of free parameters and n is the sample size. As known, given an information criterion, the best model is that with the smallest value.

A further criterion is also considered, which takes into account the sharpness of the posterior classification of units into latent classes. For this purpose, G index is adopted (see Montanari et al. 2018; Bartolucci et al. 2018), obtained for each k (hence denoted by G_k) as follows:

$$G_k = \frac{\sum_{i=1}^{n}(\tilde{p}_i - \frac{1}{k})}{n(1 - \frac{1}{k})},$$

where $\tilde{p}_i$ is the maximum posterior probability of unit i:

$$\tilde{p}_i = \max_{c=1,\dots,k} P(c|\mathbf{y}_i), \tag{6}$$

while $P(c|\mathbf{y}_i)$ is obtained as reported in (2). Index G_k ranges from 0 (random classification for all the units, with constant posterior probability for every class, equal to $1/k$) to 1 (clear classification with posterior probability equal to 1 for one class).

In Table 2 results about the selection of k are reported. For each model with k latent classes (from 1 to 12), the values of the three information criteria mentioned above are shown, together with the relative difference (%) between each value and that of the previous model with $k-1$ latent classes, while the last column reports index G_k for each model.

According to Table 2, as expected, information criteria would lead us to select a large number of latent classes ($k = 11$ with the BIC, $k = 12$ or higher using the AIC and $k = 10$ through the CAIC). As these solutions do not guarantee model parsimony (in fact, some latent classes exhibit a certain degree of overlap in terms of conditional response probabilities and, therefore, an unclear distinction between resulting profiles), we seek to find another value for k leading to meaningful results, without compromising the unit posterior classification, and assuring a reasonable compromise between goodness of fit and model parsimony.

To this aim, we plot the values of the information criteria in function of k, as depicted in Fig. 1. As it can be seen, the three curves reach the minimum for $k > 10$, but becomes almost flat at $k = 5$, implying that the improvements in terms of model fitting become lower and lower as the number of latent classes increases (i.e., especially from $k = 5$ to $k = 12$). In the same respect, in Table 2, by looking at the relative change (%) between the information criteria of two consecutive models (obtained from models with k and $k-1$ latent classes, respectively), it can be appreciated that the relative improvements in terms of model fitting are negligible for k equal or greater than five. Furthermore, the model with $k = 5$ allows us to have

Table 2 Selection procedure for the number of latent classes (k): number of free parameters (m), maximised model log-likelihood ($\hat{l}$), values of the three information criteria (BIC, AIC and CAIC) together with the relative difference between two consecutive models (%) and degree of sharpness related to the posterior classification of the units (G_k)

| k	m	$\hat{l}$	BIC		AIC		CAIC		G_k
			Value	%	Value	%	Value	%	
1	31	− 50,973.4	102,196.8	–	102,008.8	–	102,227.8	–	–
2	63	− 46,681.1	93,870.3	− 8.148	93,488.2	− 8.353	93,933.3	− 8.114	0.925
3	70	− 45,451.7	91,467.8	− 2.559	91,043.3	− 2.615	91,537.8	− 2.550	0.891
4	77	− 45,020.2	90,661.5	− 0.882	90,194.5	− 0.932	90,738.5	− 0.873	0.876
5	84	− 44,740.6	90,158.6	− 0.555	89,649.2	− 0.605	90,242.6	− 0.547	0.831
6	91	− 44,584.0	89,901.9	− 0.285	89,350.0	− 0.334	89,992.9	− 0.277	0.792
7	98	− 44,457.7	89,705.7	− 0.218	89,111.3	− 0.267	89,803.7	− 0.210	0.806
8	105	− 44,365.1	89,577.0	− 0.143	88,940.2	− 0.192	89,682.0	− 0.136	0.771
9	112	− 44,285.3	89,473.7	− 0.115	88,794.5	− 0.164	89,585.7	− 0.107	0.758
10	119	− 44,248.5	89,456.8	− 0.019	88,735.1	− 0.067	89,575.8	− 0.011	0.728
11	126	− 44,219.1	89,454.4	− 0.003	88,690.3	− 0.050	89,580.4	0.005	0.716
12	133	− 44,195.2	89,462.9	0.010	88,656.3	− 0.038	89,595.9	0.017	0.709
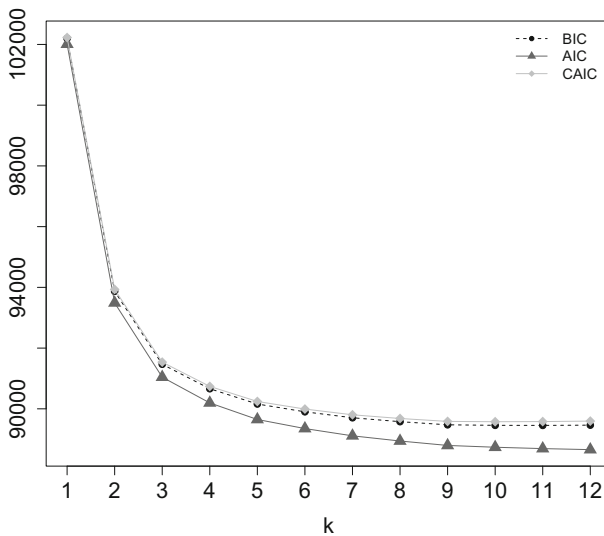
Fig. 1 Information criteria in function of the number of latent classes (k)

a good degree of posterior classification of the units, as $G_5 = 0.831$. For the above reasons, we choose the model with $k = 5$ latent classes and then consider five profiles of Millennials as regards their spare time use habits.

Each profile can be qualified by the latent trait estimates for units in latent class c, denoted by vector $\hat{\boldsymbol{\theta}}_c = [\hat{\theta}_{c1}, \hat{\theta}_{c2}, \ldots, \hat{\theta}_{c6}]^\top$ with $c = 1, \ldots, 5$. Each component of this vector represents the latent trait estimate with respect to each of the six dimensions reported in Table 1. In Table 6 (in the "Appendix") the latent trait estimates are reported for each latent class c (profile), after their standardisation through the following formulas, for $d = 1, \ldots, 6$ (Bartolucci et al. 2012):

$$\hat{\mu}_d = \sum_{c=1}^{5} \hat{\theta}_{cd} \hat{\pi}_c, \tag{7}$$

$$\hat{\sigma}_d = \sqrt{\sum_{c=1}^{5} (\hat{\theta}_{cd} - \hat{\mu}_d)^2 \hat{\pi}_c},$$

$$\hat{\theta}_{cd}^* = \frac{\hat{\theta}_{cd} - \hat{\mu}_d}{\hat{\sigma}_d}. \tag{8}$$

Finally, in Table 7 it is possible to appreciate the item parameters of the final model, that is, the discrimination and difficulty parameters. Their standardisation is here opportune due to the multidimensionality of our data, in order to compare item parameters across different dimensions. Given the mean and the standard deviation of each dimension d—see (7) and (8)—the standardised item parameters are obtained as follows, for $j \in J_d$ and $d = 1, \ldots, s$ (Bartolucci et al. 2012):

$$\hat{\psi}_j^* = \frac{\hat{\psi}_j - \hat{\mu}_d}{\hat{\sigma}_d},$$

$$\hat{\lambda}_j^* = \hat{\sigma}_d \hat{\lambda}_j.$$

Since the estimated latent trait levels are of difficult interpretation, to describe and characterise the resulting five profiles we employ the estimated conditional probability of having dimension d for units belonging to latent class c (denoted by $\bar{\hat{\phi}}_{d|c}$), with $d = 1, \ldots, 6$ and $c = 1, \ldots, 5$. They can be obtained as the mean of the estimated conditional probabilities $\hat{\phi}_{j|c}$ in (5) over the items belonging to J_d (i.e., the set of items measuring dimension d), with $d = 1, \ldots, 6$. For example, looking at the first dimension "Socialising entertaining" (measured by items in J_1, i.e., items 9, 20, 22 and 25), from (5) we can obtain the following 5×4 matrix containing the estimated conditional response probabilities for each of the four items at issue (in column) and for each of the five latent classes c (in row):

$$\begin{array}{c} \begin{array}{cccc} 9 & 20 & 22 & 25 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array}\!\!\left(\begin{array}{cccc} 0.952 & 0.013 & 0.431 & 0.147 \\ 0.977 & 0.038 & 0.702 & 0.256 \\ 0.993 & 0.166 & 0.926 & 0.486 \\ 0.994 & 0.205 & 0.942 & 0.526 \\ 0.997 & 0.382 & 0.976 & 0.657 \end{array}\right) \end{array}$$

By taking the means of each row of this matrix (equal to 0.386, 0.493, 0.643, 0.667 and 0.753), we get the "average" response probability of having the first dimension ("Socialising entertaining") for units belonging to each latent class ($\bar{\bar{\phi}}_{1|c}$). Afterwards, by repeating the same procedure for the other dimensions, we can obtain the "average" probabilities reported in Table 3. This table is the baseline for commenting the results and providing the description of the five profiles of Millennials in terms of their spare time use, as discussed in the following section.

3.4 Profiles of Millennials in spare time use

As already mentioned, conditional probabilities $\bar{\bar{\phi}}_{d|c}$ are reported in Table 3: resulting profiles can be observed by separately looking at each column of the table and are depicted in Fig. 2. The last row of Table 3 refers to the estimates of the prior probability of each latent class, which gives information on the composition of the sample according to the five latent classes.

Table 3 Personality profiles for Italian Millennials as regards free time use. Each column is a specific profile, characterised by the probability of having each of the six dimensions ($\bar{\bar{\phi}}_{d|c}$), reported in each cell. The prior probability estimates of each class, $\hat{\pi}_c$, are reported in the last row

| Dimension d	Latent class c				
	1 Inactives	2 Middle technological devotees	3 Technological laggards	4 Technological devotees	5 All-round actives
Socialising entertaining	0.386	0.493	0.643	0.667	0.753
Technologically socialising	0.194	0.620	0.283	0.750	0.732
Sportive	0.216	0.380	0.482	0.569	0.595
Technologically engaging	0.114	0.340	0.210	0.525	0.577
Individually engaging	0.117	0.160	0.383	0.362	0.536
Socially engaging	0.012	0.032	0.215	0.114	0.571
$\hat{\pi}_c$	0.129	0.174	0.104	0.343	0.250
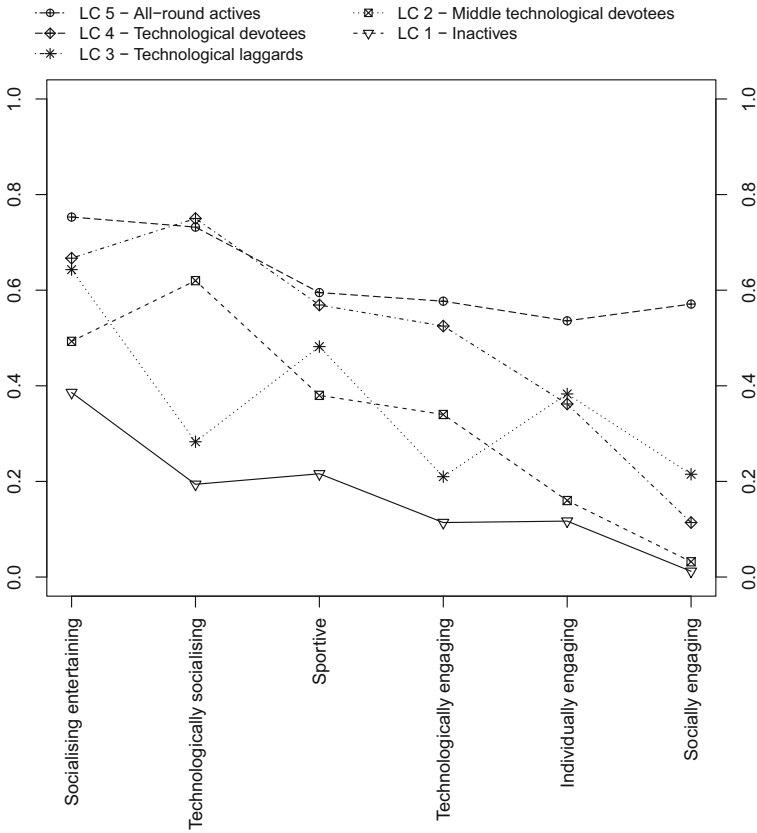
Fig. 2 Graphical representation of the five profiles of Millennials as regards time and media use. Each line is a profile, characterised by values of $\bar{\phi}_{d|c}$ (on the y-axis) with respect to each of the six dimensions, reported on the x-axis

By inspecting the five profiles reported in Table 3 and Fig. 2, it can be noted that latent class 1 qualifies a group of individuals with the lowest level of engagement (i.e., the lowest $\bar{\phi}_{d|c}$) in any of the involved activities and includes around 13% of the sample. Units in this group are then labelled as *Inactives*. Vice versa, latent class 5 is composed by Italian Millennials with the highest level of engagement in any of the six leisure dimensions accounted for in this study. This profile groups 25% of our sample. The time use dimensions that especially characterise such profile, which is the second largest group in the sample after latent class 4, are those labelled as "Socialising entertaining" and "Technologically socialising". As argued in Gnaldi and Del Sarto (2018), the former groups activities such as hanging out with friends, going to the cinema and watching live sport shows, and thus presupposes an active use of time for amusing and socialising, by sharing it with friends in traditional manners. The second clusters activities implying the use of technology such as chatting, social networking, listening to web radio, watching TV programs, films or

videos in streaming, playing or downloading games, pictures, films and music. Overall, individuals clustered in latent class 5 are named as *All-round actives*, given their high involvement in any of the six dimensions characterising time use.

Latent class 4 is the biggest group, as over one individual out of three belongs to it. Such profile shows a similar time use behaviour with respect to latent class 5, but a much lower level of involvement in both the dimensions labelled as "Individually engaging", which mostly refers to activities devoted to reading and attending recovering courses, and "Socially engaging", which mostly concerns active and open-space cultural activities, such as visiting museums and going to the theatre. By inspecting Table 3 and Fig. 2, it can be further appreciated that latent class 4 shows the highest $\bar{\bar{\phi}}_{d|c}$ (equal to 0.750) over the five profiles as regards the "Technologically socialising" dimension and the second highest value for $\bar{\bar{\phi}}_{d|c}$ (equal to 0.525) as regards the "Technologically engaging" dimension. Overall, the trait that mostly contributes to characterise this profile is the high level of technology usage, both for socialising purposes (i.e., activities clustered in the "Technologically socialising" dimension) and for individual purposes (i.e., activities included in the "Technologically engaging" dimension). Accordingly, individuals grouped in latent class 4 are then qualified as *Technological devotees*.

The profile associated with latent class 2—which includes around 17% of the sample—is comparable to that of latent class 4, as the lines associated with the two profiles follow the same trend and are substantially parallel. However, the line for latent class 2 is translated down with respect to that of latent class 4. Thus, Millennials clustered in latent class 2 show patterns of time use assimilable to those belonging to latent class 4, but with a general lower involvement in all the time use dimensions accounted for in this study. Units clustered in class 2 are then qualified as *Middle technological devotees*.

Finally, latent class 3 groups 10% of the sample and is composed by Millennials showing generally a low involvement in the activities implying the use of technology, both for socialising and for recreational purposes. This profile is clearly distinguishable from the others due to its fluctuating trend along the six dimensions, while the other four profiles are characterised by decreasing values of the $\bar{\bar{\phi}}_{d|c}$. Therefore, overall latent class 3 internal composition is very different to the other profiles, much more variable, and characterised by intermediate levels of engagement in all the time use activities but those implying the use of technology, which show low values for $\bar{\bar{\phi}}_{d|c}$. Accordingly, individuals grouped in latent class 3 are labelled as *Technological laggards*.

3.5 Further characteristics of the five profiles

In order to further qualify the five ascertained profiles (beyond the six dimensions of spare time use), a cross-classification of the sample of Millennials is performed, by concurrently considering their posterior classification in one of the five profiles—using Eq. (6)—and some personal characteristics obtained from the "Multipurpose survey on households". In particular, the following variables are included: gender,

geographic residence (Northwest, Northeast, Central, South and Insular), education level (university degree, high school diploma, lower secondary school diploma, or lower) and professional status (employed, looking for work, student, other).

Table 4 reports the composition (%) of each Millennials' profile according to the above variables, while the overall composition within the sample is shown in the last column (age-unadjusted percentages). As it can be noticed, females are slightly fewer (46.9%) than males in the overall sample. The proportion of females is lower in the two "technological" profiles, that is, the *Middle technological devotees* and the *Technological devotees*, although only in the latter we can observe a significant difference with respect to the overall female proportion. On the other hand, within the *Technological laggards* and the *All-round actives*, female proportions are significantly greater than overall.

When looking at the geographic residence, a predominance of Millennials living in the Southern/Insular Italy is generally observed (45.8%), while the rest of the sample is almost equally split over the Northern and Central regions of the country. Of course, this pattern reflects the different age structure of Italian regions. This overall picture is "heightened" in the *Inactives* profile, as 62.2% of them lives in the Southern/Insular Italy, as well as in the *Middle technological devotees* (54.9%). On the other hand, *All-round actives* are almost equally distributed over the four areas, with only a mild prevalence of Millennials living in the Southern/Insular regions (29.8%).

Table 4 Composition (%) of the five profiles of Millennials according to gender, geographic residence, education level and professional status (the proportions significantly different—at 5%—from the overall proportion are reported in *italic*)

	Inactives	Middle technological devotees	Technological laggards	Technological devotees	All-round actives	Overall
Total Millennials	415	536	322	1105	802	3180
Female	50.4	42.5	*52.8*	*41.9*	*52.4*	46.9
Northwest	*12.5*	16.8	17.1	16.6	*22.9*	17.7
Northeast	*12.0*	*11.9*	18.6	21.1	*26.9*	19.6
Central	13.3	16.4	16.5	16.0	*20.3*	16.9
South and Insular	*62.2*	*54.9*	47.8	46.3	*29.8*	45.8
University degree	*2.7*	*2.6*	4.0	4.0	*10.0*	5.1
HS diploma	*42.9*	*56.0*	60.9	67.4	64.1	60.8
LSS diploma (or lower)	*54.5*	*41.4*	35.1	*28.6*	*25.9*	34.1
Employed	27.5	25.6	*31.4*	26.2	*14.6*	23.8
Looking for work	*36.9*	*37.7*	23.0	20.7	*7.6*	22.6
Student	*20.0*	*33.6*	*43.8*	51.9	*77.1*	50.2
Other	*15.7*	3.2	1.9	*1.2*	*0.7*	3.4

HS high school; *LSS* lower secondary school

As expected, given the age of our sample units, the analysis based on account of Millennials' education level shows that more than half of the sample (60.8%) is made of people with a high school degree, while a little proportion has a university degree (5.1%). Compared to this overall picture, in the *All-round actives* profile a significantly higher proportion of Millennials with a university degree and a significantly lower proportion of Millennials with a lower secondary school diploma are observed. Vice versa, the *Inactives* and the *Middle technological devotees* are two profiles characterised by a prevalence of Millennials with low educational levels.

As to the professional status, it can be observed that while in the overall sample half of the Millennials (50.2%) are students, the corresponding proportion is 77.1% in the *All-round actives* profile, and 20.0% and 33.6% in the least engaged profiles (i.e., *Inactives* and *Middle technological devotees*), in which most of the Millennials is seeking for a job (with corresponding proportions significantly different from the overall picture).

4 Conclusions

This paper focuses on a particular population segment, that of Millennials (also known as Generation Y), which has caught much attention over recent years. We pay our attention to the use of spare time of such generation, analysing its behaviour and highlighting the predominant profiles of use of free time as regards the Italian context. In so doing, we account for the call of the literature to avoid studying time use habits across the whole population, which would lead to average results flattening peculiar time usage patterns associated with specific population segments. To this aim, we employ the "Multipurpose survey on households: aspects of daily life", a national survey administrated yearly by the Italian National Institute of Statistics, which collects a huge amount of information about several aspects of citizens' daily life, including information on spare time habits. Specifically, considering the focus on Millennials, we consider the subset of such data comprising people aged between 18 and 24.

Time use attitude is a latent phenomenon: it cannot be directly observed, but it can be analysed by exploiting a direct manifestation of it, such as the response pattern to a set of questionnaire items about time use. Moreover, time use has a multidimensional facet, since it is composed by several and related aspects, or dimensions, which contribute to characterise the general phenomenon. Previous research in this regard (Gnaldi and Del Sarto 2018) revealed that six dimensions have to be accounted for when considering attitude towards use of free time in Italian Millennials. However, the picture provided by that research refers to an "average" Generation Y individual. As such, it does not allow us to portray patterns of time use behaviours and, consequently, to catch different profiles of Italian Millennials, each characterised by a distinctive use of spare time, according to the six ascertained dimensions. To this aim, in the present paper we rely on the latent class multidimensional IRT model (Bartolucci 2007), which allows us for a clustering of the statistical units (Millennials, in our case) into groups (the latent

classes) on account of a latent phenomenon (attitude towards time use), by considering at the same time its multidimensional nature.

Our main findings reveal that the way Italian Millennials use time and interact with the new media and technology differs very much on account of the considered dimensions of time use. On this ground, we identify five profiles of Millennials branded with distinctive time use behaviours. Among them, we can observe two extreme profiles characterised by a uniform behaviour along all the six leisure dimensions accounted for in this study. The first, which counts for a quarter of our sample of Italian Generation Y individuals, shows a high level of involvement in each of the time use activities accounted for in this study and is consequently qualified as *All-round actives*. On the other side, the *Inactives* profile comprises around 13% of the sample and includes Millennials with the lowest level of engagement in all the time use activities characterising the ascertained six dimensions. The analysis devoted to qualify Millennials' profiles on account of individual characteristics—i.e., gender, geographic residence, education level and professional status—shows that, compared to the overall sample, the *All-round actives* is a profile made mainly of highly educated Millennials, residing in the northern and central regions of the country, and in a student condition. Vice versa, the *Inactives* profile shows a mirror image, as it is composed mainly of Millennials seeking for a job and residing in the least developed southern regions of the country. Overall, these two extreme profiles are those for which we observe the most significant differences across individual characteristics with respect to the whole sample of Generation Y people.

The bulk of Italian Millennials, comprising around 60% of the sample, is represented by three intermediate profiles, for which the use of technology has a diriment role when aiming at differentiating them. In the *Technological devotees* profile, as well as in the *Middle technological devotees* profile of Millennials, the use of technology for socialisation purposes—i.e., for posting messages in chats and social networking—is the preferred dimension of time use. However, when the use of technology comes into play as an activity meant to engage in information acquisition and to share political and social views, it becomes a much less crucial time use activity for both the previous profiles, and especially for the latter. This is also true for the remaining profiles accounted for in this study. The third intermediate profile (*Technological laggards*), despite its small size (only 10% of the sample), is an interesting and atypical profile, which clusters Generation Y people with a very low interest in technology, either for socialising and for information acquisition, compared to the other time use activities accounted for in this study.

When accounting for individual characteristics to qualify these latest profiles, it emerges that the *Technological devotees* and *Technological laggards* profiles—which are very similar but for a very different attitude toward the use of Internet and technology—differentiate each other especially on account of their composition by gender and professional status. Specifically, the group of *Technological devotees* is made by a lower than average proportion of females. Vice versa, the group of *Technological laggards* is made by a higher than average proportion of employed males. Therefore, according to these results, the different occurrence of IT-use

activities among Italian Generation Y people is more associated to their professional status than to education level. At first glance, this could appear as a foregone conclusion given the young age of our sample, but it is not. In fact, the composition by education level of the other Generation Y profiles is very different one another (and the corresponding proportions significantly different from the overall sample).

Compared to the general perception conveyed by mass media—portraying Millennials as a generation of IT-confident young people with low engagement in social capital activities and civic participation, little cultural commitment and weak social ties—our study reveals a more complex picture. In line with that part of the literature—see for instance, Burke and Kraut (2014) and Hampton et al. (2011); Hampton (2016)—indicating that IT use is associated with having a larger number of core social ties, we can summarise our main outcomes as follows.

Firstly, not all Italian Millennials are IT-confident and prefer to devote their spare time to IT-related activities. In fact, the use of Internet and technology for socialising purposes comes into view as the most important time use dimension for two profiles of Millennials out of the five accounted for, the *Technological devotees* and the *Middle technological devotees* (accounting for roughly 50% of the sample). Besides, the use of technology for information acquisition (i.e., downloading newspapers, news, magazines) and to share political and social views (i.e., by posting political opinions or attending consultations) is not a prevalent time use activity for any of the five Millennials' profiles. Finally, the *Technological laggards* profile clusters Generation Y people with a very low interest in technology compared to the other spare time activities.

Secondly, Italian Millennials do engage in social capital activities and cultivate their social ties. In fact, *All-round actives*, *Technological laggards* and *Inactives* profiles have the "Socialising entertaining" dimension—referring to a use of time to socialise and have fun, by sharing it with friends in a non media-mediated manner— as their favourite one. What is more, also for the remaining Millennial profiles, the "Socialising entertaining" dimension is among the preferred spare time activities. More than an extensive use of technology, these outcomes highlight that socialisation—either in a way not mediated by the media (i.e., hanging out with friends) or through the use of technology (i.e., sending or receiving e-mails, calling/videochatting, posting messages in chats, social networking)—is the beloved time use choice of Italian Millennials.

Finally, Italian Millennials tend to show a low engagement in activities related to civic participation and cultural commitment. In fact, overall, activities clustered in the "individually engaging" dimension—such as participating in private courses (i.e., on art, culture, foreign languages) and reading newspapers, magazines, periodicals—and in the "socially engaging" dimension—including traditional cultural activities such as going to the theatre or museums, and visiting archaeological sites or monuments—come into account as the least relevant facet of time use for all the Generation Y profiles. However, this general finding is moderated by a further concurrent outcome of our study, which shows that all the ascertained profiles (but the *Technological laggards* one) display an average engagement in media-mediated cultural activities, such as downloading newspapers,

news, magazines from the web and sharing political and social views by posting political opinions or attending online consultations.

The present work has some limitations and can be extended in several ways. First, the reported analyses do not consider the evolution over time of the phenomenon under study. As the ISTAT Multipurpose survey is conducted every year, different waves can be considered in order to assess the invariance over time of our results. Furthermore, another recent survey on this topic, called "Uso del tempo" and carried out by ISTAT (ISTAT 2018), could be taken into consideration. The exploration of the potentials of these data will be carried out in future developments of our work, also in view of further validating the present results.

Appendix

See Tables 5, 6 and 7.

Table 5 Content of the 31 selected items within the "Multipurpose survey on households" with the percentage of affirmative responses (%)

Item ID	%	Content	Original label	No. of categories
1	2.89	Participation in scholastic recovering courses or private lessons	A45	4
2	2.58	Participation in computer science courses or private lessons	A46	4
3	3.71	Participation in foreign languages courses or private lessons	A47	4
4	2.45	Participation in courses or private lessons on artistic and cultural activities	A48	4
5	50.44	Having a period of holidays longer than four nights in the last year	A99	2
6	35.38	Continuous sport activity	A110	2
7	15.66	Occasional sport activity	A111	2
8	22.36	Physical activity different from sport (e.g., walking, a swimming)	A112	4
9	98.62	Hanging out with friends	A116	7
10	72.45	Listening to the radio	A189	3
11	92.14	Watching television	A192	3
12	75.03	Watching VHS and/or DVD	A195	6

Table 5 continued

Item ID	%	Content	Original label	No. of categories
13	80.57	Using Internet for at least one of the following activities:		
		Sending or receiving e-mail	A222	2
		Calling/videochatting	A223	2
		Posting messages in chats, social networks, blogs, newsgroups or on-line discussion forums and using instant messaging services	A224	2
14	39.28	Using Internet for at least one of the following activities:		
		Reading or posting opinions about social or political problems	A225	2
		Online attendance to consultations or votes about social or political problems	A226	2
15	68.33	Using Internet for at least one of the following activities:		
		Reading or downloading newspapers, news, magazines	A227	2
		Looking for information about goods and services	A228	2
		Booking doctor appointments	A229	2
		Using trips and accommodations services	A230	2
		Using banking services	A232	2
16	60.63	Using Internet for at least one of the following activities:		
		Listening to the web radio	A233	2
		Watching TV programs on web	A234	2
		Watching films in streaming	A235	2
		Watching videos in streaming	A236	2
17	56.70	Using Internet for at least one of the following activities:		
		Playing or downloading games, pictures, films, music	A237	2
		Online games	A238	2
18	49.28	Using Internet for at least one of the following activities:		
		Uploading self-created contents	A239	2
		Building web sites or blogs	A240	2
		Selling goods or services	A231	2
19	27.20	Using a portable device (different from computers) for at least one of the following activities:		
		Sending or receiving e-mails	A257	2
		Reading or downloading newspapers, news, magazines	A258	2
		Reading or downloading books or e-books:	A259	2
		Playing or downloading games, pictures, videos, music	A260	2
		Social networking	A261	2
		Other activities	A263	2
20	19.12	Using a portable device (different from computers) for at least one of the following activities:		
		Getting information from web sites	A267	2
		Downloading pre-edited forms	A268	2
		Filling pre-edited forms	A269	2

Table 5 continued

Item ID	%	Content	Original label	No. of categories
21	22.52	Going to the theatre	A301	5
22	84.15	Going to the cinema	A302	5
23	34.72	Going to museums, exhibits, etc.	A303	5
24	46.89	Going to classical music concerts or operas, or other music concerts	A304-A305	5
25	45.88	Watching live sport shows	A306	5
26	69.28	Going to dance	A307	5
27	23.62	Visiting archaeological sites and/or monuments	A308	5
28	49.62	Reading daily newspapers at least once a week	A309	5
29	52.77	Reading non-school and/or non-professional books	A310	2
30	43.27	Reading weekly magazines	A312	4
31	24.84	Reading non-weekly periodicals	A313	2

Table 6 Standardised latent trait estimates for each latent class c

Dimension	Latent class c				
	1	2	3	4	5
Socialising enterteining	− 1.896	− 1.047	0.202	0.399	1.072
Technologically socialising	− 2.142	0.149	− 1.247	0.676	0.588
Sportive	− 2.064	− 0.864	− 0.125	0.616	0.870
Techologically engaging	− 2.229	− 0.183	− 0.826	0.584	0.815
Individually engaging	− 1.615	− 1.179	0.312	0.186	1.265
Socially engaging	− 1.557	− 0.901	0.314	− 0.117	1.458

Table 7 Estimated IRT parameters from the final model with $k = 5$: standardised discrimination and difficulty parameters ($\hat{\lambda}_j^*$ and $\hat{\psi}_j^*$, respectively)

Item ID	Dimension	$\hat{\lambda}_j^*$	$\hat{\psi}_j^*$
9	Socialising entertaining	0.909	− 5.189
20	Socialising entertaining	1.300	1.443
22	Socialising entertaining	1.338	− 1.689
25	Socialising entertaining	0.810	0.271
8	Technologically socialising	0.016	76.473
11	Technologically socialising	0.387	− 6.544
13	Technologically socialising	2.438	− 1.121
16	Technologically socialising	2.141	− 0.082
17	Technologically socialising	2.149	0.047
18	Technologically socialising	2.250	0.269
6	Sportive	0.536	1.216
7	Sportive	0.313	5.489
12	Sportive	0.880	− 1.436
26	Sportive	0.945	− 0.987
1	Technologically engaging	0.600	6.082
10	Technologically engaging	0.367	− 2.710
14	Technologically engaging	1.729	0.504
15	Technologically engaging	2.510	− 0.359
19	Technologically engaging	1.900	0.863
2	Individually engaging	0.718	5.367
4	Individually engaging	1.085	3.823
5	Individually engaging	0.774	− 0.011
24	Individually engaging	1.191	0.171
28	Individually engaging	0.843	0.039
29	Individually engaging	1.210	− 0.088
30	Individually engaging	0.676	0.456
31	Individually engaging	0.886	1.465
3	Socially engaging	0.926	3.934
21	Socially engaging	1.256	1.294
23	Socially engaging	2.295	0.476
27	Socially engaging	2.156	0.986

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