Which Indicator Best Measures Cultural Engagement? A Comparative Analysis

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Which indicator best measures cultural engagement? A comparative analysis

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ABSTRACT

Culture plays a central role in society. It supports inclusion, identity, and civic participation, while also contributing to economic activity and political engagement. Therefore, using appropriate tools to measure Cultural Engagement (CE) is crucial. In this paper, a set of composite indicators to measure cultural participation is developed, starting from individual participation in a range of cultural activities. Traditional methods—such as weighted and unweighted averages and Principal Component Analysis (PCA)—and a different approach based on Item Response Theory (IRT) are compared. These methods are examined in terms of interpretability and key features, looking across Italian regions and population subgroups, with attention to economic resources, education and gender. The analysis relies on nine waves (2014–2022) of the *Aspects of Daily Life* survey by the Italian National Institute of Statistics (ISTAT). While classical methods tend to be more intuitive and easier to read, the IRT-based approach offers distinct advantages, especially when analyzing individual cultural activities. Overall, the IRT approach enriches a body of literature that has, so far, offered limited tools for measuring CE.

1. Introduction

Culture plays a central role in our society. It promotes social inclusion, freedom of expression, identity-building, and civic empowerment, while also contributing to economic development and encouraging political participation and engagement [1,2]. Cultural capital is traditionally understood as a multifaceted concept encompassing several dimensions [3,4]. For these reasons, it is essential to use appropriate tools to measure cultural engagement and participation. However, the literature on this field has often measured cultural engagement by considering just one or two cultural activities and hardly considers more of them together [4]—e.g., visits to museums and archaeological sites [5]; museum and monument attendance [6]; art exhibitions [7]; and visits to museums and jazz concerts [8].

In this multidimensional context, the use of measurement tools capable of handling such complexity appears plausible. One possible strategy is to rely on composite indicators. These composite measures are widely used in statistical and economic research [9,10]. A composite indicator synthesizes a complex system made up of several dimensions, facilitating a more intuitive interpretation [11]. In the case of Cultural Engagement (henceforth CE), where participation spans a broad range of activities, each influenced by distinct social, economic, and individual factors, composite indicators could offer the advantage of summarizing diverse behaviors into a single, coherent metric.

In this paper, a set of composite indicators to assess CE is proposed. Classical approaches commonly used in the literature are compared with an alternative method based on Item Response Theory (IRT) [12,13]. Among classical strategies, various aggregation techniques based on weighted means, weighted sums and Principal Components Analysis (PCA) are considered. IRT, by contrast, provides a probabilistic framework for measuring latent traits from categorical items, ensuring greater methodological consistency [14]. This approach not only improves the reliability of indicator construction but also helps identify the most relevant dimensions of CE [15,16]. Some of the classical composite indicators approaches (weighted mean, weighted sum and PCA) and the IRT one are analyzed, trying to answer the following research questions: *Are composite indicators suitable for measuring CE*? If so: *Is there a more appropriate composite indicator for this framework*?

The analysis covers both methodological and empirical perspectives. On the methodological side, the approaches are evaluated based on the procedures used to construct the composite indicators and the features they offer for data analysis. On the empirical side, the study draws on a

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unique dataset composed of nine nationally representative cross-sectional surveys conducted between 2014 and 2022 by the Italian National Institute of Statistics (ISTAT). Italy presents a particularly relevant case for the study of CE. Despite its rich cultural heritage, the country shows low levels of participation in cultural activities, ranking among the least engaged nations in Europe [17] and receiving below-average cultural funding compared to other European countries [18]. The selected time frame allows for an observation of CE encompassing the COVID-19 pandemic. This period provides an opportunity to examine the relationship between external shocks and cultural participation. In addition, composite indicators are compared using an heterogeneity analysis, aimed at identifying differences across subpopulations, based on key determinants of CE.

The remainder of the paper is structured as follows. Section 2 outlines the background literature on cultural capital, cultural consumption, and existing approaches to measuring CE. Section 3 presents the data and describes the methodologies used to construct the CE indicators. Section 4 reports the results of the comparative analysis of the different methods used to construct the CE indicators. Section 5 concludes with a discussion of key findings and implications.

2. Measuring cultural engagement: the background

In the field of cultural economics, researchers have long focused on studying the demand side [19]. Among the earliest economic characterization of cultural capital, cultural assets are distinguished into two types [3]. *Tangible assets* are physical objects or places, like buildings and artworks. *Intangible assets* are non-material—shared ideas, traditions, and meanings. Both play a role in how culture is valued and used. Cultural participation is seen as a factor that contributes to the development of both *tangible* cultural capital, by supporting the production of new cultural objects, and *intangible* cultural capital, by strengthening social behaviors and practices that hold cultural meaning [20].

Research on cultural participation and cultural consumption has traditionally seen it as a multidimensional concept, aiming to create diverse cultural profiles based on the activities in which people participate [4,21]. However, empirical cultural research often treats CE in parts, focusing on one or two activities at a time [6–8]. A comprehensive examination of cultural participation entails an integration of different aspects of cultural consumption. Only with a comprehensive measurement approach is possible to understand who takes part in culture and why [4]. Consequently, it can be challenging to measure it [22].

Some studies take a broader approach by combining different aspects of cultural activity into one measure. For instance, by measuring how often people took part in cultural activities over time—twelve months in [18], six in [23]. In both cases, they build a simple score by adding up how many times each person joined things like museum visits, exhibitions, or classical concerts. Other studies look at museum visits along with other cultural activities [17,24]. But in both papers, the data does not allow them to take the activity types apart. A more advanced approach employs survey data and PCA to examine 19 variables capturing different forms of cultural participation [25]. They find three components explaining around 40 % of the total variance, they label these components in the following way: highbrow cultural events, popular shows, and sports. They find that participation is more related to economic resources while tastes to social capital.

Past research has consistently identified the key factors that shape cultural participation [26]. Education and income have been found to represent the strongest predictors across European countries [17]. Among these, education emerges as the most frequently cited factor in the literature [8,27,28], with higher levels of education shaping personal tastes and fostering greater interest in highbrow cultural activities [21]. Also income has been found to be positively related to cultural participation [25]. For example, a study examining cultural attendance across 13 major Chinese cities—including visits to museums, libraries, galleries, and cultural centers—found that income has a positive effect on cultural participation [29]. However, they also show that in cities with higher average wealth, income matters less. A gender differential is also commonly found in the literature, showing that women are usually more culturally engaged than men [30–32]. A possible explanation relies on the early exposition to art. Girls usually attend more art classes than boys in childhood, and this early artistic familiarization could explain over a quarter of the gender gap [33].

Moreover, COVID-19 pandemic had a clear effect on cultural participation in the Italian context, due to the lockdowns all over the country. The role of digitalization during the pandemic has been investigated, showing a sharp rise in online cultural material and initiatives through social media, with museums doubling their online activity [34]. However, there is also contrasting evidence, as digital activities (e.g., reading a digital book or following a museum on social media) did not change much during the pandemic in Denmark [35].

In the subsequent paragraph, the data and the methodology are shown. Considering data, the survey questions used to construct the composite indicators, and the estimation sample used to test the CE measures are shown. In the methods section, the analytical framework is introduced, together with the formulation of the composite indicators.

3. Data and methods

3.1. Data and estimation sample

This study relies on a large-scale dataset that enables a comprehensive comparative analysis of Italy over the 2014–2022 period. The data come from nine harmonized waves of the *Aspects of Daily Life* (AVQ) multipurpose household surveys conducted by the ISTAT. These are nationally representative cross-sectional surveys carried out annually, involving interviews with approximately 20,000 households and 50,000 individuals each year.

The surveys followed a two-stage sampling strategy. In the first stage, municipalities—used as primary sampling units—were selected using probability proportional to size without replacement. In the second stage, households were selected with equal probability, without replacement. The survey design included stratification at the level of the primary units. The average response rate across all waves exceeded 80 %, ensuring strong representativeness of the Italian population.

CE measures are computed using survey questions that ask respondents about their participation in a set of cultural activities over the past 12 months. As these questions are retrospective, each survey wave is considered as referring to the previous year. The six cultural activities considered are: going to theatres, going to cinemas, attending classical music concerts, attending other music concerts, visiting monuments or archaeological sites, and visiting museums or exhibitions. Respondents' answers are recorded as ordinal categorical variables on a scale from 1 to 5: 1 – Never, 2 – From 1 to 3 times, 3 – From 4 to 6 times, 4 – From 7 to 12 times, 5 – More than 12 times.

The estimation sample consists of individuals aged from 18 to 75 years old, living in Italy. Only individuals who responded to the relevant survey questions are included. Individuals younger than 18 are excluded, as their CE typically reflects that of their parents. Those older than 75 are excluded due to generally lower participation rates in cultural activities. This approach is consistent with prior research [17,18]. The final sample comprises 281,403 respondents across eight survey waves (2014–2022). The data are structured as repeated cross-sections, with different individuals surveyed in each wave. The number of respondents varies by wave, with an average of 31,342 observations per wave, ranging from 29981 individuals (in 2020) to 34504 individuals (in 2017).

3.2. Cultural engagement measures

CE is measured using several widely applied methods from the literature on composite indicators. Four approaches are considered: the unweighted mean, a weighted mean, a weighted sum, and a methodology based on IRT. Each of these strategies is described in the following paragraphs.

3.2.1. Classical approaches

The most straightforward and commonly used method is to calculate the mean—weighted or unweighted—of individual ordinal categorical scores [10]. Choosing the weights is a critical step, as it determines the relative importance assigned to each cultural activity. There are several approaches to assigning weights [36]. Considering the two mean-approaches, one simple option is to apply equal weights across all cultural activities, implicitly treating each as equally relevant. Alternatively, different weights can be assigned to reflect varying degrees of importance among activities. One possibility is to set weights based on findings from previous literature. An example is the educational indicator used as a subcomponent of the Human Development Index, giving 2/3 weight to the literacy rate and 1/3 to the combined gross enrolment rate [36]. However, this approach introduces a degree of subjectivity from the researcher.

A formalization of these two strategies can be the following. Considering an individual j belonging to a population N ($N \in \mathbb{N}$). Then, consider a set H of cultural activities X_i, such that $H = \{X_1,\ldots,X_i,\ldots,X_D\}$. X_i are ordinal categorical variables such that X_i can take the following values: $X_i = [1,2,3,4,5]$. Given our six cultural activities, a CE indicator is given by:

$$CE_j = \frac{\sum_{i=1}^{6} w_i x_{ij},}{\sum_{i=1}^{6} w_i}, \tag{1}$$

where x_i represent one of the six cultural activities score and w_i are weights assigned to each cultural activity. As previously mentioned, two weight settings are proposed. First, a simple unweighted mean is considered. In this case, weights are set as: $w_i = 1$ for all i. Second, an arbitrary choice of weights is considered, following evidence from the literature. In this case, since numerous works give a larger importance to the visit of museums or exhibitions and the visit to monuments and archaeological sites [5,8,17], weights for these two cultural activities are set as 0.3 while for all the others 0.1 In this way weights are subject to the constraint of $\sum_{i=1}^{6} w_i = 1$.

Another widely used method for constructing a composite indicator is to compute a weighted sum of normalized scores across the different cultural participation dimensions. In this approach, the weighting process is data-driven, allowing the data itself to give the relative importance of each dimension. One of the most common techniques in this context is PCA [10,37,38], which identifies the principal components that capture the shared variance among the various cultural activities. If the first principal component explains a sufficiently large portion of the total variance, the corresponding loadings (i.e., the correlations between each activity and the principal component) can be used as empirical weights. Considering the framework introduced before, the composite indicator score for the individual, is given by:

$$CE_j = \sum_{i=1}^{6} w_i x_{ij}, \tag{2}$$

Since for all waves there is a principal component explaining a large part of the total variance (always close to 50 % of the total variance), weights can be set equal to the loadings. In this way, weights are chosen to maximize the variance of the CE measure [38], with the constraint: $\sum_{i=1}^{6} w_i^2 = 1$. With this approach, a specific weight is assigned to a single dimension for each wave, and it is equal for all individuals belonging to that wave. However, weights differ from one wave to the other.

3.2.2. An alternative approach

An alternative methodological framework frequently employed in the literature is IRT. IRT represents a probabilistic modeling approach used to estimate unobserved (latent) traits through categorical variables, which can be either dichotomous or ordinal in nature [12,13,39]. The technique relies on a logistic function to model the likelihood of a given response, incorporating both item-level parameters and characteristics of the respondent.

In this analysis, the two-parameter logistic 2 PL model introduced by Ref. [40] is applied. Consider a population of N individuals j ($N \in \mathbb{N}$). The 2 PL model is then defined as follows:

$$P(X=1|\theta,a,b) = \frac{e^{a(\theta-b)}}{1+e^{a(\theta-b)}}. \tag{3}$$

In this framework, the variable X stands for the unobserved response to a particular item, where a value of $X = 1$ denotes a correct or affirmative response, and $X = 0$ denotes an incorrect or negative one. The latent trait, represented by θ, captures the unmeasured attribute for individual i. The parameter b describes the item's difficulty, essentially, the level of θ required to have a higher likelihood of responding positively to the item. Conversely, parameter a measures how well the item discriminates between individuals who differ in their latent trait. To interpret the estimated parameters, Item Characteristic Curves (ICCs) are typically used. These curves illustrate how the likelihood of a correct response to an item varies across different levels of ability (θ). The horizontal position of the curve represents the item's difficulty, whereas the steepness of the curve signifies how well the item distinguishes between individuals of differing abilities. A higher inflection point indicates a more challenging item, while a sharper slope denotes greater discriminative power.

Within this study, θ is interpreted as the level of individual CE ($CE = \theta$), and X refers to engagement in a specific cultural domain. Here, a gauges how widespread participation is, while b reflects the activity's ability to differentiate engagement levels. The ICC thus illustrates how the likelihood of engaging, in a given cultural activity, shifts across varying degrees of CE. For simplicity, answers are reframed as 6 dummy variables where 1 represents if the individual has participated at least once in the cultural activity and 0 if the individual did not participate. These variables represent the items X.

Several methods are available for estimating the latent trait θ (see Ref. [41]). The Empirical Bayes (EB) approach is applied here, as detailed by [42]. This method estimates θ by taking the mean of its empirical posterior distribution. Within this framework, model parameters—represented as B—are replaced with their estimated values $\widehat{B}$, which is why the method is referred to as "empirical"; the estimates are treated as fixed. The EB approach combines the prior distribution of the latent variable with the data-driven likelihood function to derive the posterior distribution. For each individual j, the estimate is based on this empirical conditional posterior distribution of the latent trait. The approach is described by the following formula:

$$\omega(x_j;\widehat{B}) = \frac{f(x_j \mid \widehat{B},\theta_j)\ \varphi(\theta_j)}{L_j(\widehat{B})}, \tag{4}$$

where x_j are the observed answers to X of the person j, $\widehat{B}$ is the parameters estimate, $L_j(\widehat{B})$ is the contribution to the maximum likelihood function of j, $\varphi(\theta_j)$ is the function describing the latent trait. The prediction of θ is calculated by resolving the following integral:

$$\widehat{\theta}_j = \int_{-\infty}^{+\infty} \theta_j \omega(x_j;\widehat{B})\ d\theta_j. \tag{5}$$

Here, $\widehat{\theta}_j$ represents the predicted latent trait. Since in this setting the individual's latent trait represents the CE, then the estimated CE $(\widehat{CE_j})$ is equal to $\hat{\theta}_j$. This integral is approximated through the *Mean–Variance Adaptive Gauss–Hermite Quadrature* algorithm.

4. A comparison across cultural engagement measures

The classical and alternative approaches are compared in terms of their interpretability and the methodological features they provide. The following subsections include a spatio-temporal analysis of the four composite measures, an heterogeneity analysis, and an evaluation of the contribution of each cultural activity to the overall indicator.

Fig. 1a–d presents a graphical representation of the evolution of CE indicators across Italian regions. Regional CE values are computed as weighted averages of the proposed composite indicators, using the sampling weights provided by the AVQ survey. Specifically, Fig. 1a displays the unweighted mean indicator, Fig. 1b the arbitrarily weighted version, Fig. 1c the PCA-weighted indicator, and Fig. 1d the IRT-based indicator. The maps are arranged chronologically from left to right, illustrating the situation in 2018 (pre-COVID-19 period), 2020 (during the first lockdowns and the peak of the pandemic), and 2021 (when lockdown measures were less restrictive and daily life began to normalize).

All four measures reveal very similar spatial patterns, with a consistent North-South gradient: Southern regions systematically show lower levels of CE across all indicators. Temporally, the effect of the pandemic is clearly visible, with 2020 recording the lowest levels of engagement. Although there is a rebound in 2021, cultural participation does not return to pre-pandemic levels—likely due to the continued presence of moderate restrictions and a general sense of caution among the population.

From the perspective of interpretability, the classical indicators are the most straightforward. For the unweighted and arbitrarily weighted means, the minimum possible values correspond to the average of the weights, providing a clear lower bound for interpretation. For the PCA-based indicator, since the cultural dimensions are rescaled in the [0, 1] range, the minimum value is set to 0. For all three classical indicators, theoretical maximum values were not used in the legends, as these tend to be unrealistic. Instead, the maximum values were set based on the observed distributions of each indicator.[1] For example, in the unweighted mean, a value of 1.5 might indicate participation in three different cultural activities between one and three times, or intensive participation in one activity and moderate engagement in another. In contrast, the IRT-based indicator is more complex to interpret: the estimated latent scores ($\widehat{CE} = \hat{\theta}$) theoretically range within in the interval $(-\infty, +\infty)$, making interpretation less intuitive. These scores are best understood in relative terms, allowing comparison across regions within the same metric, rather than providing a fixed benchmark of CE.

4.1. A sub-groups analysis

This analysis considers the main determinants of cultural participation identified in previous literature, comparing the four composite indicators in capturing differences across population groups. Educational level is categorized into three groups: *Primary* (primary and lower secondary education), *Secondary* (upper secondary education), and *Tertiary* (tertiary education or higher). Current economic status is measured through a survey item in which respondents describe their financial situation for the current year.

The survey question is the following: "*Regarding the last 12 months and considering the needs of all family members, how were your family's overall financial resources?*". Possible answers are *great, adequate, scarce, absolutely insufficient.*

Fig. 2 presents the weighted means of CE indicators over time, disaggregated by educational level. Across all indicators, trends are quite similar and show a clear, persistent gradient: CE increases with higher levels of education. In the pre-pandemic period, engagement trends are relatively stable. However, in 2020 with the arrival of the pandemic, a significant drop in participation is observed, followed by a partial recovery in the subsequent year—though not enough to reach pre-pandemic levels. This pattern holds across all three educational groups.

Additional analyses are presented in Appendix A: Fig. A1 examines differences by economic resources, while Fig. A2 focuses on gender. In both cases, trends across composite indicators remain closely aligned. Regarding economic status, CE is higher among individuals with greater disposable income. Notably, disparities in CE appear to widen at higher income levels. For example, using the PCA-based composite indicator, the difference in average pre-pandemic engagement between those with "great" and "adequate" resources is 0.12 (0.39 vs. 0.27), whereas the gap between "scarce" and "absolutely insufficient" is just 0.04 (0.17 vs. 0.13). This suggests that cultural participation may rise more sharply with increased economic resources, pointing to a nonlinear association.

When comparing sexes, data show that women were more culturally engaged than men prior to the pandemic. However, after the sharp decline in engagement caused by the pandemic, the levels of participation do not return to their original state—and the pre-existing gender differential appears to diminish or disappear.

4.2. An analysis of single cultural activities

Composite indicators inevitably involve a loss of information from the dimensions they aggregate. This is a well-known trade-off in the literature: while some granularity is sacrificed, composite measures offer the major advantage of interpretability by summarizing complex, multidimensional phenomena into a single, easily understandable indicator [10,43]. A reliable composite indicator is one that balances this trade-off effectively, maximizing interpretability while minimizing information loss. Nonetheless, it is standard practice to complement composite indicator analysis with an examination of trends in the individual dimensions. This is especially important in the context of CE, as cultural activities differ substantially from one another—not only in terms of content and form but also in the demographics they attract [4].

In the case of the analyzed classical approaches, the typical method is to examine the trends of each cultural activity separately and compare them across time or subgroups. However, the IRT approach offers a more reliable solution through the use of ICCs, which allows to evaluate the contribution of each dimension directly within the model. In this framework, the two key parameters—b (difficulty) and a (discrimination)—capture the role of each cultural activity X_i in estimating the latent trait θ, which in this case reflects overall CE. ICCs plot the probability of participating in a specific activity (at least once in the past year) as a function of θ. The curve's horizontal position represents the difficulty parameter (b), indicating the level of engagement required for an individual to participate. The steepness of the curve reflects the discrimination parameter (a), which shows how well the activity distinguishes between individuals with different levels of CE. Activities with higher inflection points are more difficult to access (less attractive), while those with steeper slopes are more informative in differentiating between individuals' CE.

Table 1 presents the estimates for parameters a and b, while Fig. 3 displays the ICCs. The analysis begins considering parameter b. Among all activities, attending classical music concerts is the most difficult ($b = 1.77$), followed by going to theaters ($b = 1.23$) and attending other music concerts ($b = 1.23$). These results indicate that classical music

[1] This is because of the coding of the ordinal categorical variables describing the cultural activities. They range from 1 to 5. A value of 1 means participating to the cultural activity from once to three times and 5 means more than 12 times. Since regional means are compared, it is unrealistic to assume than on average people go more than 12 times in each cultural activity. The theoretical maximum is equal to 5 in the mean-related indices. For the PCA is equal to the sum of weights, that is always close to 2.5, depending on the weights setting for each wave.

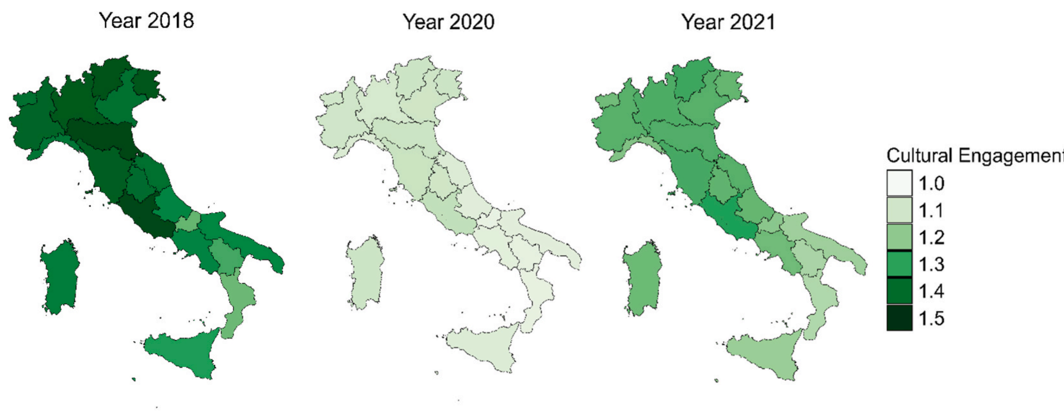

Fig. 1a. Mean estimations of individual cultural engagement scores in the Italian regions using the unweighted mean composite indicator. *Source*: 2014–2022 waves from *Aspects of Daily Life* survey.

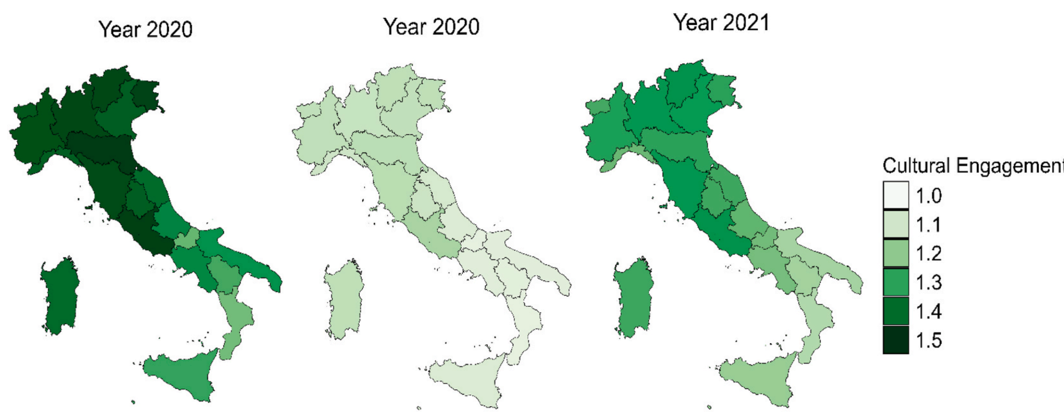

Fig. 1b. Mean estimations of individual cultural engagement scores in the Italian regions using the weighted mean composite indicator. *Source*: 2014–2022 waves from *Aspects of Daily Life* survey.

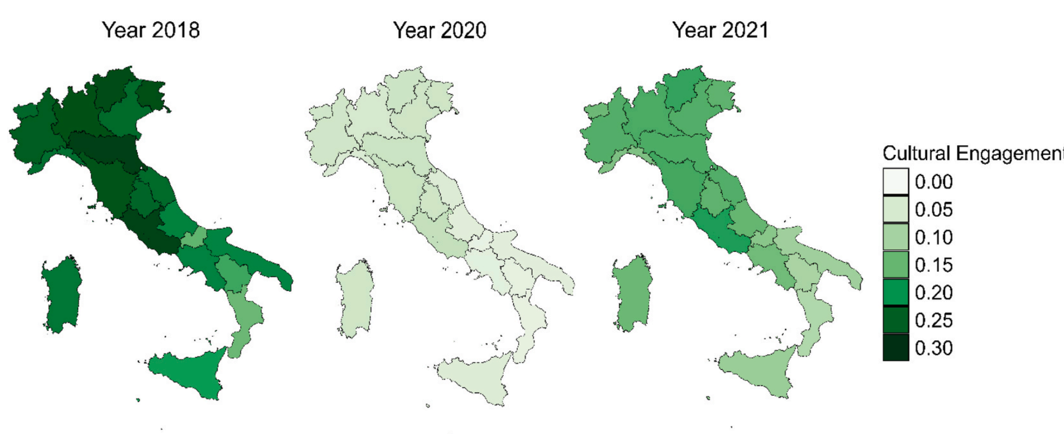

Fig. 1c. Mean estimations of individual cultural engagement scores in the Italian regions using the PCA-weighted indicator. *Source*: 2014–2022 waves from *Aspects of Daily Life* survey.

concerts have the lowest participation, making them more exclusive forms of CE. Turning to a, cinemas and non-classical music concerts exhibit the lowest discriminability ($a = 1.60$ and $a = 1.66$, respectively). This suggests that these activities do not strongly distinguish between individuals with low and high engagement levels. In contrast, visiting museums and exhibitions emerges as the most discriminating activity ($a = 6.61$), followed by visiting archaeological sites or monuments ($a = 3.23$), meaning they provide a more relevant differentiation across individuals' CE.

Another important strength of the IRT-based approach lies in its ability to evaluate which cultural activities are most appropriate for measuring CE. Prior studies propose a practical rule of thumb for selecting suitable items: A cultural activity is considered a reliable predictor of the latent trait if its difficulty parameter (b) falls within a specific range. Items with very low values are too widespread and fail to distinguish levels of engagement, while those with very high b values are

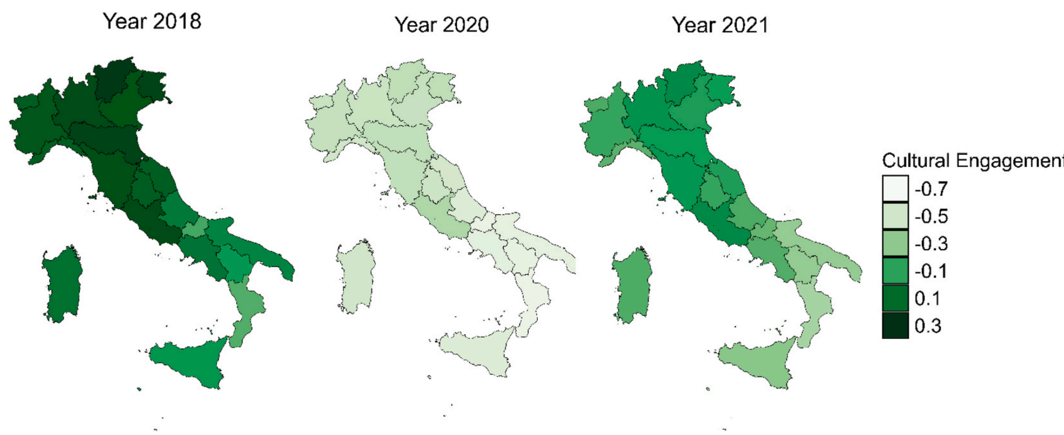

Fig. 1d. Mean estimations of individual cultural engagement scores in the Italian regions using the IRT composite indicator. *Source*: 2014–2022 waves from *Aspects of Daily Life* survey.

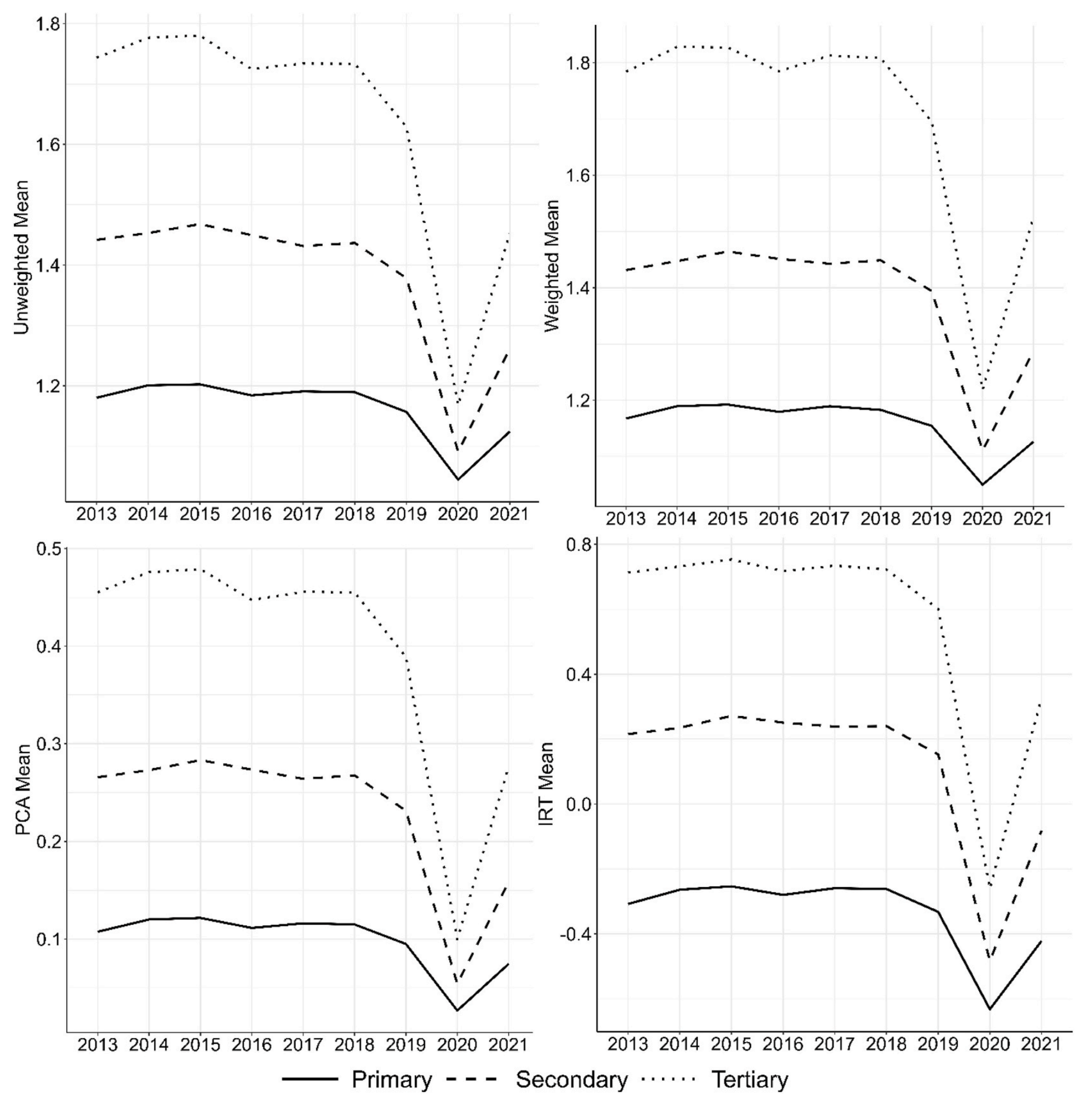

Fig. 2. Weighted means trends of cultural engagement composite indicators over time across educational levels. *Source*: 2014–2022 waves from *Aspects of Daily Life* survey.

too rare to provide meaningful variation.

Following prior research [15,16], the recommended range of $[0, 3]$ is adopted. Fig. 1 visually illustrates the spread of difficulty parameters across the selected activities. The item with the lowest inflection point is cinema ($b = 0.255$), while classical music has the highest ($b = 1.77$). Since all activities fall within this acceptable range, each activity

Table 1
Estimated difficulty and discriminability for engagement in cultural activities considering the IRT indicator. Results from the 2 PL model.

Variable	Coefficient	Std error	z	p-value	Confidence interval 95 %	
Cinemas						
Discriminability	1.606732	0.0107071	150.06	<0.001	1.585747	1.627718
Difficulty	0.2551843	0.0038223	66.76	<0.001	0.2476926	0.2626759
Archaeological sites						
Discriminability	3.234747	0.0244483	132.31	<0.001	3.18683	3.282665
Difficulty	0.7699316	0.0035128	219.18	<0.001	0.7630465	0.7768166
Music Concerts						
Discriminability	1.667259	0.0113422	147.00	<0.001	1.645029	1.689489
Difficulty	1.239051	0.0061351	201.96	<0.001	1.227027	1.251076
Classical music concerts						
Discriminability	2.043249	0.0160145	127.59	<0.001	2.011861	2.074637
Difficulty	1.772345	0.008389	211.27	<0.001	1.755903	1.788787
Museums						
Discriminability	6.616352	0.1008321	65.62	<0.001	6.418724	6.813979
Difficulty	0.60482	0.0027358	221.07	<0.001	0.5994579	0.6101821
Theatres						
Discriminability	2.143828	0.0150695	142.26	<0.001	2.114292	2.173364
Difficulty	1.239717	0.0054694	226.67	<0.001	1.228997	1.250437

Note: These are parameter estimates computed on the estimation sample. *Source*: 2014–2022 waves from *Aspects of Daily Life survey*.

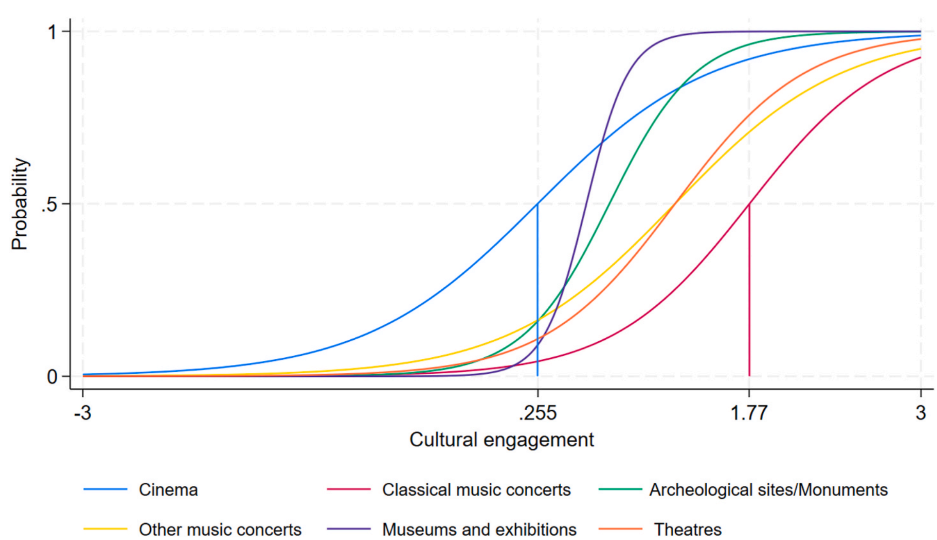

Fig. 3. Item Characteristic Curves on cultural engagement. *Source*: 2014–2022 waves from *Aspects of Daily Life* survey.

contributes valid information to the measurement of CE.

5. Discussion and conclusion

This paper focuses on the measurement of CE, a various and diverse phenomenon [21]. Its diverse nature seems to relate well with a composite indicators approach. This paper advances a set of composite CE measures, and compared them considering various perspectives. We believe this paper contributes to the literature for at least three reasons.

First, regarding our initial research question — whether a composite indicator is suitable for measuring cultural engagement — this approach enables the simultaneous consideration of multiple dimensions, whereas previous studies have typically focused on only one or two cultural aspects [6–8]. Adopting such an approach allows for a more comprehensive and nuanced understanding of cultural engagement.

Second, a set of classical composite indicators of CE is considered, together with an approach not previously applied in this literature. On one side, traditional methods such as weighted averages and factor analysis are employed. On the other, a more advanced method based on IRT is implemented. The comparison shows that classical indicators offer greater interpretability, producing results on a scale with clear theoretical minimum and maximum values. While the IRT indicator is less straightforward to interpret, it positions all individuals on a common scale, enabling comparisons across survey waves and population groups. This feature is particularly useful for analyzing long-term trends.

The IRT approach stands out from the others for two main reasons, one methodological, one substantive. From a methodological perspective, it relies on a probabilistic model that estimates CE as a latent trait for each individual, based on the probability of participating in specific cultural activities. This framework provides a statistically stronger and more reliable structure for individual-level estimates compared to more traditional methods. Moreover, as the number of cultural activities (i.e., the items in the IRT model) increases, the precision of CE estimates improves correspondingly. The probabilistic nature of the model also offers considerable flexibility. For instance, it can be extended to more complex cultural contexts that account for multiple levels of aggregation through the use of Multilevel Item Response Theory models, which have been widely developed and applied in other research domains [14,44,45]. From a substantive perspective, a common critique of composite indicators is that they hide too much detail by reducing variability into one number [9–11,43]. IRT solves part of this problem. It still gives a single indicator, but the value is based on a probabilistic model that also shows how each activity contributes to the composite score. The representation used in the ICCs implements this feature in two ways. The position of the curve tells how common or rare a given activity is, while the slope shows how strongly it distinguishes between more and less engaged individuals. A steep slope indicates that the activity is particularly useful in capturing differences in cultural engagement. This level of detail also helps evaluate whether the chosen activities are appropriate for measuring cultural participation. As a rule of thumb, if the position of the ICC lay within the interval of from 0 to 3, we can be more confident that the activity plays a real part in shaping the final indicator [16,17].

Third, we offer new empirical evidence on the determinants of cultural participation for the Italian context. The heterogeneity analysis—conducted by region, educational attainment, economic resources, and gender—reveals clear and consistent patterns. Across all composite indicators, a pronounced effect of the COVID-19 pandemic emerges, with a clear decline in CE observed across every subgroup. The intertemporal analysis presented in Fig. 1a–d shows that, by 2021, CE levels have not returned to their pre-pandemic values in any Italian region. This pattern suggests that although a partial recovery occurred following the first lockdown period, it was insufficient to restore cultural engagement to previous levels. The limited rebound can likely be attributed to several factors. On one hand, the reintroduction of restrictive measures and localized lockdowns during 2021 continued to limit opportunities for in-person cultural participation. On the other, the lingering sense of uncertainty and fear among consumers—driven by concerns about public health, income stability, and social interaction—likely discouraged individuals from re-engaging fully in cultural and social activities [46–51].

From a regional perspective, a distinct gradient is evident: individuals residing in the North demonstrate higher levels of cultural participation compared to those in the South. Both educational attainment and economic resources are positively associated with CE, with particularly pronounced differences among higher economic strata. Regarding gender, women generally exhibit higher cultural participation than men, although this disparity vanishes following the pandemic-related disruption. Further insights into the post-pandemic evolution of this trend may be obtained through the analysis of more recent survey waves.

As with many empirical investigations, this study is subject to certain limitations, primarily related to the characteristics of the available data. The reliance on repeated cross-sectional surveys restricts the possibility of tracking individuals over time. This prevents the application of longitudinal methods capable of capturing how CE evolves across the life course—an approach particularly relevant for analyzing patterns shaped by early exposure and persistent habits. Additionally, the granularity of the data on cultural activities poses a constraint. A more extensive range of items would enhance the implementation of the IRT model, allowing for greater precision in estimating the CE score. Nevertheless, the use of an IRT-based methodology is considered to offer substantial benefits. It enables a structured and transparent representation of individual differences in cultural participation. In this regard, the IRT-based indicator provides a substantial contribution to cultural studies by offering a more statistically robust approach for measuring cultural engagement compared to traditional composite indicators.

CRediT authorship contribution statement

Alessandro Gallo: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Francesca Adele Giambona:** Writing – review & editing, Supervision, Resources, Methodology, Formal analysis, Conceptualization. **Daniele Vignoli:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization.

Declaration of competing interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.seps.2025.102379.

Data availability

The datasets generated and analyzed during the current study are publicly available at https://www.istat.it/microdati/aspetti-della-vita-quotidiana/.

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