Journal of Cultural Economics (2023) 47:643–692
https://doi.org/10.1007/s10824-022-09466-3

ORIGINAL ARTICLE

Live and digital engagement with the visual arts

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Received: 13 November 2018 / Accepted: 24 November 2022 / Published online: 26 December 2022

Abstract

The cluster of innovations brought about by information and communication technology (ICT) is dramatically changing the ways in which the visual arts can be produced and consumed. By using the USA 2012 Survey of Public Participation in the Arts, we explore visual arts consumption through both onsite attendance at museums and electronic and digital media. To disentangle the complexity of the relationship of different forms of museums attendance, both a multinomial logit and a recursive bivariate probit model are estimated to obtain direct and indirect effects of the alternative forms of participation. Results demonstrate that there are no age consumer differences in the form they consume visual arts. Noticeable differences concern race, gender, families with children attending arts school, and type of occupation. In addition, results show that there is a trade-off between online and onsite visits. Visiting museums and art galleries have a positive correlation with the digital access to visual arts, both through handheld and mobile devices and via the internet, whilst the same correlation is not found for internet access on museum attendance. This means that for many consumers, online attendance is the only way to overcome time constraints and other costs involved in an onsite visit.

Keywords Cultural participation · Digital engagement · Live and online museum visits · Handheld or mobile devices · Internet

JEL Classification C55 · D12 · Z11

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1 Introduction

Information and communication technology (ICT) has profoundly transformed the way cultural products and services are produced, distributed, and consumed and, apart from transforming each one of the aforementioned dimensions, it has also blurred the distinction between them. Terms such as prosumption or produsage describe the new hybrid types of cultural engagement (Bruns, 2013; Navarrete & Borowiecki, 2016; Sánchez Olmos & Viñuela, 2020), and the electronic and digital media consumption of cultural goods has become a more common habit for the general population than live attendance, even before the Covid-19 lockdowns that have only accentuated the already increasing trend of online digital offerings by cultural institutions. For example, according to data for the USA taken from the 2012 Survey of Public Participation in the Arts (2012 SPPA), 37% of the population attended a live performance and 39% some visual arts event or activity at least once in the previous year, whereas 71% consumed art through some form of electronic media: TV, radio, internet, handheld or mobile devices, DVD, CD, tape, or record player (NEA, 2013). Given that participation through the media has grown, some of the traditionally well-known facts concerning the determinants of cultural participation, such as the ageing of audiences, could be challenged, and new research questions should be addressed.

Accordingly, the relationship between different means of cultural engagement needs further attention. Alternative forms of participation are not necessarily competing with or even "cannibalising" each other, but very often appear to be either successive or simultaneous complements. ICTs are present before, during, and after the enjoyment of a physical visit to a museum, shaping expectations and modelling different experiences (Kuflik et al., 2015; Marty, 2007). Visitors seek information to make an informed decision about what to attend. They complement their visit with digital cultural products (such as apps), and they may later extend the experience by making use of digital channels for further exploration, based on the memories and reflections derived from the visit. As a matter of fact, in some cases, digital engagement can turn into a more active way of participation than the actual visit itself (Barnes & McPherson, 2019), enlarging the visitor space for creative and active involvement (as in co-creation or co-curatorship).

Digitalisation has also extended participation to a wide range of cultural goods. Among all the possible artistic activities, this research concentrates on museums and the visual arts. Visual arts are one of the more popular cultural activities in the USA in terms of cultural engagement, as measured in the 2012 SPPA. During 2012, 59% of US adults went at least once to the cinema, 39% to visual arts, and 37% to some performing arts event or activity (NEA, 2013). Electronic and, more importantly, digital access to content related to the visual arts are increasing and have already surpassed visits in terms of popularity. In 2012, for example, an estimated 7.9% of US adults engaged with the visual arts through handheld devices or mobiles, a proportion similar to engagement through TV or radio, and slightly higher than via the internet (NEA, 2013). This is due to the rapid diffusion of new technologies in everyday life, with around 71% of the population using the internet and 53.1% using handheld or mobile devices. Despite these diffusion rates, differences in computer ownership and internet access still persisted by age (favouring youngest individuals), race and ethnic origin, income, and education (File, 2013; Pick et al., 2015). Mobile devices and internet have potentially different audiences, whilst the consumption of internet from some location other than the computer at home is the highest among all age groups, for younger people (18–34) desktop usage has decreased. Connectivity is modelled as a "continuum" that goes from multiple locations and devices to no connection at all. Using data from the Current Population Survey, July 2011, it is found that connectivity also depends on age, race and origin, income and education (File, 2013; Pick et al., 2015). However, visual art is a topic in which relatively little research has been conducted compared to other areas (e.g. music), where the impact of electronic media and digital access and piracy has aroused more interest, helping to define the cultural consumption patterns of internet users.

This paper aims to fill this lacuna by jointly investigating the determinants of the choice of attendance at museums and art galleries and of digital engagement with visual arts through handheld or mobile devices and via the internet. Whilst both refer to information and communication technologies, some differences between them may emerge. To this purpose, we use data taken from the 2012 edition of the Survey of Public Participation in the Arts to estimate both multinomial logit and recursive bivariate probit models (hereafter SUR-Biprobit) for museum attendance and the consumption of content through handheld devices and/or internet. The use of the two approaches helps us to both estimate the probability to attend different forms of visual arts, and the potential cross-effect between onsite and digital participation.

Different ways of engagement in visual arts are explained in terms of variables that account for differences in demographics, personal cultural capital and education, labour market status and occupation, socio-economic characteristics, disability, and geographical variables. The estimation results of both models show that socio-economic conditions, tastes, and, above all, education determine participation in both models. However, differences emerge when considering the impact that different resources (income and time) have on one or other type of engagement: onsite and digital. Museum-going increases the probability of both accessing visual arts content on mobile devices and via the internet, whilst the consumption of visual arts on handheld or mobile devices and through the internet does not have a significant effect on the probability of onsite visiting museums and art galleries. The main contribution of this work to the existing literature is that it jointly studies the demand for visual arts through attendance at museums and electronic and digital media, including an attempt to understand the relationship between the two.

The remainder of the work is structured as follows. Section 2 analyses alternative ways of accessing cultural goods. The data and the methodological approaches are discussed in Sect. 3. Results and discussion are presented in Sect. 4. Finally, Sect. 5 concludes the paper with a discussion.

2 Conceptual framework

The consumption of cultural goods for a pleasant cultural experience is a time-intensive activity, no matter which medium is chosen (live attendance, artistic practice or media consumption); the individual has to dedicate a remarkable amount of time and cultural capital to it (Castiglione & Infante, 2016). However, there are some differences among the ways those resources are allocated. Unlike visits to museums and art galleries, virtual and electronic media access to cultural institutions renders it technologically possible to grant an easier access to them. The convergence of cultural experiences has given audiences the chance to access their choice from anywhere and whenever they wish, breaking down the barriers of time and place (Bakhshi & Throsby, 2010) and improving the experience through interactivity and connectivity. Technology has dramatically changed the market for the arts, especially in terms of the expansion and diffusion of culture, given that more materials are available to more people (Tepper et al., 2008). Digitalisation raises the possibility that arts and cultural organisations can overcome the traditional constraints imposed by physical location, thereby expanding their outreach (Bakhshi & Throsby, 2010; NEA, 2010). For instance, given that museum attendance tends to be highly seasonal (Johnson, 2003), online attendance could decrease this seasonality. Furthermore, ICTs have created better access to museums by using apps and virtual or augmented reality systems to enrich the onsite visiting experience (Ateca-Amestoy, 2013; Navarrete, 2013). The demand for museums is not therefore linked to place or location, and cultural goods may be consumed anytime and anywhere (Ateca-Amestoy & Prieto-Rodríguez, 2013; NEA, 2010). On the other side, the consumption of cultural goods through ICTs can be negatively influenced by the digital divide. Several studies have contributed to a better understanding of the digital divide in the arts (for example, Norris & Inglehart, 2013), gathering evidence of the existence of a gender gap on the internet (Bimber, 2000; Ono & Zavodny, 2003), of age barriers potentially linked to a decline in cognitive ability in old age (Freese et al., 2006), and of the emergence of a digital distinction due to differential payoffs from internet use depending on a user's socioeconomic background (Zillien & Hargittai, 2009).

From the supply side perspective, cultural content can be embedded in new tangible and intangible goods or in traditional formats that can be produced and distributed using new technologies. Digitalisation alters the relative prices of alternative ways of accessing culture and cultural goods themselves when compared to other substitutes and complements (Potts, 2013). Moreover, ICT enables cultural goods to be produced more cheaply, leading to a reduction in price and a consequent expansion in the size and diversity of audiences (Starr, 2004).

The determinants of onsite cultural attendance have been studied for different activities, whilst less is known about the determinants of participation in the arts through digital devices, with the major exception of music and cinema, which are probably the two industries most affected by illegal digital access. Nevertheless, this is an important question for understanding cultural engagement as the use of ICTs has become crucial in different aspects of daily life. It is also relevant from a cultural manager's point of view, as institutions should provide both onsite and online content and services to cultural audiences.

When analysing live and digital participation, there are two main issues to be studied. Firstly, the determinants of each type of engagement (are the determinants of electronic consumption similar to those of physical participation?). Secondly, the links between digital and physical participation (are they substitutes, complements, or wholly unrelated?). The complementary or substitute nature of different means of access to cultural goods and of different art forms has been explored, and the literature has still not found any conclusive evidence. On the one hand, online visits should open the door to the whole society; on the other hand, physical visits could be abandoned to the benefit of virtual visits (Evrard & Krebs, 2018).

Few authors have tried to study the relationship between onsite and online consumption. Nguyen et al. (2014) show that the consumption of music through streaming services (such as Spotify or YouTube) has no impact on the consumption of physical music (such as CDs and live music) among a representative sample of internet users. This can be interpreted as evidence supporting new business models that exploit streaming and other forms of dematerialised cultural goods.

On the other side, Montoro-Pons and Cuadrado-García (2011) find a high complementarity between attending popular music concerts and listening to recorded popular music, with live concerts creating a demand for recorded music. The same relationship is also found by De la Vega et al. (2020), who show a complementarity effect between live and online highbrow performing arts. Even though a relationship is found, there is no evidence of cannibalisation in the links between the attendance of live theatre performances and the broadcasts of the UK's National Theatre Live (Bakhshi & Throsby, 2014). Although the Bakhshi and Throsby' study (2014) is different from the aim of this research, not only because it refers to theatre and cinema and not to visual arts, it is interesting to report because it explores whether live broadcasts of theatre to digital cinemas substitute for or complement audiences for traditional theatre. From a quasi-field experiment of the Royal National Theatre's NT Live broadcast of the production Phèdre, they find that the live broadcast is a complement for physical theatre attendance. Using another source of evidence to study the same programme, Bakhshi and Whitby (2014) conclude, in fact, that "live simulcast" has probably boosted local theatre attendance in those areas that have been more exposed to the programme.

In this work, two alternative accesses to cultural goods that are not mutually exclusive in their consumption are considered: visits to museums and art galleries and the consumption of visual arts through handheld or mobile devices and via the internet. In what follows, we shall maintain that different technologies govern the transformation of cultural goods into those cultural experiences: attendance and media consumption. In conclusion, we can say that although most studies focus on the physical attendance of museums (Fernández-Blanco & Prieto-Rodríguez, 2011; Frey & Meier, 2006; and Johnson, 2003), despite the importance and potentiality of digital devices in participation in the arts, very few studies have been conducted in this field, and since their results are not univocal, additional research is required.

3 Data and methodology

3.1 Data and descriptive statistics

The data used in this analysis are taken from the 2012 Survey of Public Participation in the Arts (NEA, 2013). This survey is periodically run as a supplement to the Current Population Survey by the Bureau of the Census. Data for the 2012 release were collected in May 2012 from a sample of people aged over 18. This dataset compiles information on participation in the arts by US citizens. The dataset contains information on attendance at different artistic activities (jazz, salsa and Latin music, classical music, opera, musicals, plays, ballet, dance, art museums, arts and crafts, and visits to historical parks and monuments) and also covers other types of cultural practice, such as the consumption of cultural goods through the media and some types of hands-on artistic practices. A total of 37,266 questionnaires were completed by individuals over 18 for a representative sample of households in the USA. The sample was drawn up following a multi-stage strata design with clusters, based on information from the Bureau of the Census. A weighting variable makes the sample representative for the adult civilian population by age, gender, and ethnic origin.

Since 1982, the National Endowment for the Arts' Survey for Public Participation in the Arts (SPPA) has been the largest, most representative survey of adult patterns in arts participation. In 2008 and 2012, the SPPA were redesigned compared with previous releases. The idea was to better handle a number of important design issues that arose from the 2002 version. The main goal was to develop a design that would be less burdensome to survey-takers. In particular, the 2012 SPPA survey randomly sampled adults and, for many of the questions, accepted proxy responses for spouses or partners. In the 2008 and 2012 SPPA, proxy responses were clearly identified in the data file prepared by the Census Bureau. Moreover, rather than administer the entire SPPA survey to all respondents, the questionnaire was separated into modules, so that any one respondent answered only a core set of arts attendance questions and 2 other modules. In order to ensure the representativeness of the sample, appropriate weights are provided to use for various possible combinations of variables in the analysis. In any case, it is not possible to use variables from both core modules at the same time. In addition, it is not possible to use variables from more than two modules in the same runs, since no respondents answered more than two modules and using variables from two different modules will sometimes raise sample size concerns. A number of studies have been conducted in related topics with the SPPA 2012 data and are cited in the literature review paragraph (i.e. Elpus, 2018; Kaimal et al., 2016; Mauri & Wolf, 2021; and O'Hagan 2014).

Table 1 provides a detailed description of the variables used in our models. In order to consider online and physical visits to visual arts, we consider a set of dichotomous variables: *musego*, *handheld* and *internet*. *Musego* indicates the physical visit to museums, or museum-going. The variable is equal to 1 if the individual answers positively to: "*Visited an Art Museum during last 12 months*", and 0 otherwise. *Handheld* indicates the participation through handheld or mobile devices, so the variable takes the value 1 when the individual gives a positive answer to the

Table 1 Variables used in the analysis

Variable	Definition
Dependent variables	
Musego	Did you visit an art museum or gallery during the last 12 months?
Handheld	During the last 12 months, did you use handheld to view visual art online, such as paintings, sculpture, or photography?
Internet	During the last 12 months, did you use internet to view visual art online, such as paintings, sculpture, or photography?
Musehand	0 did not attend any actvities; 1 attend both; 2 attend only musego; and 3 attend only handheld
Museint	0 did not attend any actvities; 1 attend both; 2 attend only musego; and 3 attend only internet
Explanatory variables	
De—Demographic variables	
Age	Age
Sex	Female, Male
Race	Ethnic: White, Black, Indian
Cu—Educational/cultural variables	
Edu	Own education level: having tertiary education
Children_art_school	Were any of your school aged children taught art or music/(art museum or gallery or attend a live music, theater or dance performance) in school/outside school
Occ—Occupational variables	
Occup	Occupational status: employed, unemployed, not in labor force
Occu	Occupation of the worker (10 categories, according to *2010 Census Occupational Classification*)
H—Household variables	
Hinc	Household income
Marital	Marital Status: married, widowed, single, separated or divorced
Child	Number of children
Di—Health status	
Disa	Disabilities: eyes, ear, mobility, psychological…
Geo—Geographical Variables	
Central	Principal city
Balance	Balance
Nometro	Non-metropolitan
Others	not identified

Data from the 2012 Survey of Public Participation in the Arts (NEA, 2013)

following question: "*Do you use any handheld or mobile devices to download or view any visual arts such as painting, sculpture, graphic design, or photography?*", and 0 if the answer is negative. Some examples of handheld devices or mobile devices are smart phones, MP3 players, eBook readers, laptops, notebooks, and tablet computers. Finally, *internet*, indicates the digital participation and it takes a value of 1 if the individual answers positively to: "*Do you use the internet to watch, listen* *to or download any programmes or information about the visual arts, such as painting, sculpture, graphic design, or photography?*", and 0 if negative, or if the individual did not use the internet at all. Moreover, we used two other combined dependent variables: *musehand* and *museint*. Both variables take the value 0 if the person did not attend any activity; the value of 1 if the person attends both activities; the value of 2 if the person attends only *musego*; and finally takes the value of 3 if the person attends only *handheld/internet*.

3.2 Empirical model

In this paper, in order to analyse the attendance at museums both onsite and online, we apply two different modelling methods. The rationale of choosing these two approaches is that the first one in using the simultaneous logit multinomial model permits to estimate the correlation that might exist in museum attendance and the consumer's preference to attend in different forms. The second method of using the recursive bivariate probit model permits to investigate the complexity of the relationship of the modes of attendance since we can disentangle the joint (recursive) effect of the dependent variables (cross effect). In the multinomial logit model, the utility of each alternative is a linear function of observed characteristics plus an additive error terms. Individuals are assumed to choose the alternative that has the highest utility (Verbeek, 2004). The recursive bivariate probit model assumes that two dependent variables are jointly determined with a weak causation (Green 2007).

3.2.1 Multinomial logit model

Since the aim of this paper is to address the choice of individuals when consuming the visual arts, either by visiting museums and galleries (*musego*) or by digital engagement (*handheld* and *internet*), following Favaro and Frateschi (2007) and Prieto-Rodríguez and Fernández-Blanco (2000), we use a multinomial framework to simultaneously evaluate the probability of different forms of participation to visual arts. We specify a multi-choice setting where there is a single decision to make about the different form of participation to choose. With this in mind, we classify the different alternatives in the following categories:

P_{np} is the alternative of "not participate to any kind of cultural activities";

P_{od} is the alternative of "participate through digital equipment, but not onsite";

P_{oph} is the alternative of "participate only onsite, but not through digital equipment";

P_{all} is the alternative of "participate through both on-line and onsite".

The probability of choosing any possible alternative is estimated by a multinomial logit model where the probability that ith individual opt for the alternative k is equal to:

$$\begin{aligned} P_{ik} &= Prob\left(U_{ik} > U_{ij}\right) && \textit{for all } j \neq k \\ &= Prob\left(V_{ik} + \varepsilon_{ik} > V_{ij} + \varepsilon_{ij}\right) && \textit{all } j \neq k \\ &= Prob\left(\varepsilon_{ij} - \varepsilon_{ik} > V_{ik} - V_{ij}\right) && \textit{all } j \neq k \end{aligned}$$

where U_{ij} is the utility the individual obtains from any choice j, j = 1,…..,J; V_{ij} is the representative utility of the individual characteristics and of the attributes of alternative j, x_{ij}. In order to capture the aspect that are not observed, U_{ij} is decomposed into $U_{ij} = V_{ij} + \varepsilon_{ij}$.

3.2.2 Recursive bivariate probit model

To capture the twofold effect (direct and indirect) of the potential cross-effect of participation, a recursive bivariate model is used. This methodology, following Montoro-Pons and Cuadrado-García (2011) for bivariate outcomes, and Nguyen et al. (2014) for multinomial choice, is suitable for treating the endogeneity of the alternative means of access. The direct effect is captured by including one of the dependent variables as explanatory variable in the other equation, whilst the indirect effect is estimated through the tetrachoric correlation between unobserved error terms.

In estimating a recursive bivariate probit model, the problem is the correct identification of the model that is generally based on exclusion restrictions (Humphreys et al., 2014; Maddala 1983). Wilde (2000) argues that an exclusion constraint is not necessary to identify the parameters in the system of equations, provided that both equations contain a varying explanatory variable. Under the assumption of normality of error terms, the bivariate probit model is identified using the functional form; in other words, in the absence of additional instruments, the identification depends heavily on the functional form (i.e. the normality of the stochastic disturbances). Although convergence with identification can be achieved through the functional form, exclusion restrictions often improve identification. However, difficulties can be found to achieve convergence without imposing an exclusionary constraint, and identification by functional form may be empirically fragile (Jones 2007; Marra & Radice, 2011). Finally, in the recursive probit model, if the dummy variable is exogenous for the equation of interest, testing the exogeneity "requires a great deal of sample information and deteriorates sharply in the absence of exclusion restrictions, even under correct distributional assumptions" (Monfardini & Radice, 2008: 281).

An exclusion constraint in the context means that at least one exogeneous variable is excluded from the structural equation (in our case the *musego* equation) and the same variable is included in the reduced form equation (second equation). For this reason, we include in Eq. (1) the variable number of children (*Nchild*), which is significant and is theoretically grounded and does not occur in Eq. (2), whilst in Eq. (2), which measures *internet* or *handheld* attendance, we have included the variable that identifies the use of the internet and does not have any impact on Eq. (1).

The SUR-Biprobit model takes the usual form (Greene, 2007), with the dependent and independent variables corresponding to those specified in Table 1, and following the discussion presented in this section, and can be represented as:

$$y_1^* = x_1'\beta_1 + \varepsilon_1,\ y_1 = 1\ \textit{if}\ y_1^* > 0,\ 0\ \text{otherwise},$$
$$y_2^* = x_2'\beta_2 + \varepsilon_2,\ y_2 = 1\ \textit{if}\ y_2^* > 0,\ 0\ \text{otherwise},$$
$$\left(\varepsilon_1, \varepsilon_2\right) \rightarrow N_2[(0,0),(1,1),\rho]$$

with y_1 for live attendance and y_2 for *handheld* (or *internet*) consumption.

This is further complemented by the estimation of a recursive simultaneous bivariate probit (Greene & Hensher, 2010) that has the following structure:

$$\begin{aligned} y_1^* &= x_1'\beta_1 + \gamma y_2 + \varepsilon_1, & y_1 = 1\ \textit{if}\ y_1^* > 0, \quad 0\ \text{otherwise}, \\ y_2^* &= x_2'\beta_2 + \varepsilon_2, & y_2 = 1\ \textit{if}\ y_2^* > 0, \quad 0\ \text{otherwise}, \\ \left(\varepsilon_1, \varepsilon_2\right) &\rightarrow N_2[(0,0),(1,1),\rho] \end{aligned}$$

The parameters are estimated by using the following maximum likelihood function:

$$LogL = \sum_{i=1}^{n} ln\Phi(q_1 X_i'\beta, q_2 X_i'\gamma, \rho)$$

with

$$\phi\left(q_1 X_i'\beta, q_2 X_i'\gamma, \rho\right) = \int_{-\infty}^{\chi_i'\beta} \int_{-\infty}^{X_i'\gamma} \phi\left(z_1, z_2, \rho\right) dz_1, dz_2$$

with $q_j = 1$ if $y_j = 1$ and $q_j = 0$ otherwise, for $j = 1, 2$.

3.3 Empirical specification

In this paper, it is assumed that the underlying and unobserved values for y_i are such that there is a linear relationship between these explanatory variables:

$$y_i = f\left(x_i\right) = f\left(De_i,\ Cu_i,\ Occ_i,\ H_i,\ Di_i,\ Geo_i\right)$$

where y_i indicates De_i, Cu_i, Occ_i, H_i, Di_i, and Geo_i are vectors of "demographic, educational and cultural", "occupational", "household resource", "health", and "geographical" variables for the individual i, respectively.

The characteristics of the individual and the household are presented in Table 1. There are some variables that determine the taste or skills of the individual for cultural consumption, whereas a second group represents individual and context resources (such as health status, an individual resource, or household income, a resource that describes the availability of such income).

The vector of demographic variables (De_i) includes age, gender, and race. Life cycle and age effects may influence participation rates in two different ways. On the one hand, it is through the learning-by-consumption processes, which emphasise the fact that the more performances one attends, the more enjoyable they become. Also, school-based arts education is strongly associated with later arts participation as patron/consumer and performer/creator (Elpus, 2018). On the other hand, younger people are more likely to be "digital natives"; thus, a different impact on traditional and online visits could be found. Since the digital divide has a generational component, the age effect could work in favour of younger generations. This is the reason for assigning dichotomous variables for each age class. The following six dummy variables are defined: age1 (18 to 24), age2 (25–34), age3 (35–44), age4 (45–54), age5 (55–64), and age6 (65 +). Gender and ethnicity are among what Seaman (2005) calls "mixed factors" that can have an influence on both types of participation. Different experiences during childhood may play a role, e.g. boys tend to participate more in sports and less in arts and music than girls do (Katsuura, 2008). Finally, a set of dummy variables regarding the individual's ethnic group (white, black, and others) are included.

The vector of cultural capital variables (Cu_i) is included since participation in the arts is generally accepted to depend on the individual stock of cultural capital. The empirical literature finds a positive relationship between high culture, higher educational achievement, and higher income (Ateca-Amestoy & Prieto-Rodríguez, 2013; Muñiz et al., 2017; Seaman, 2005; Upright, 2004) that is used as a proxy of cultural capital. Education is expected to have a positive monotonic relationship with attendance: the higher the level of education, the higher the likelihood of a person attending the performing arts. The assumption behind this is that better-educated individuals have a greater capacity to appreciate and understand the qualities of artistic performances. Hence, the individual educational level could capture the impact of general human capital. A dummy variable equal to 1 is created for levels of education that correspond to the associate degree (occupational/vocational and academic), bachelor, master, professional school or doctorate degree; and zero otherwise. In the vector of educational/cultural capital variables, the variable, *children_art_school* (which indicates whether any school aged children are taught art or music/art or go to a museum or gallery or attend a live music, theatre or dance performance), in school or outside school is also added. The idea is that if school children attend arts event, it is likely that parents can share the same experience with them through the internet or onsite.

The vector of the socio-economic variables (*Occ*) controls for the role played by cultural engagement. People working in certain occupations may be more likely to engage both onsite and online. This is derived from the notions of "creative class", "creative industries", and "creative occupations" (Cunningham, 2011; Cunningham & Higgs, 2008; and Florida, 2001). Testing for the hypothesis that individuals of the "creative class" engage in leisure activities following the patterns described by Florida (2001), Bille (2010) finds that being a part of this "creative class" nevertheless has implications for leisure and cultural habits. Bille (2010) uses Danish data from cultural practices and occupation surveys to identify individuals that belong to the so-called "creative class" and to the "creative core". Falk and Katz-Gerro (2016) identify that professionals and managers have a higher probability of participation. Among the professional occupations, business, social science, writing, creative or performance art occupations show the highest participation in cultural visits. On the basis of this literature, the vector of socio-economic variables (*Occ*) is constructed using the occupational status (*Occup*) from the 2010 Census Occupation

Classification Codes and, for those employed, ten dummy variables (*Occu*) as shown in Table 2 are created.

When thinking about resource allocation, one must start with some measure of available income (*H*). According to the theory of demand, the positive relationship between income and participation implies that arts participation is not an inferior good and that a higher income increases demand. However, in this case it is instructive to study how participation under the two types of considered access (live and digital) may have a different behaviour. For the household income, four different variables have been built: less than USD 25,000; 25,000 to 49,999; 50,000 to 99,999; and more than 100,000. Household size, marital status, and number of children in the family (no child, one child, two children and three or more children) are also considered. All these factors play a role in determining the time available for individuals and the opportunity cost of the time dedicated to leisure activities. Time constraint determines substitution effects between leisure activities. According to McCarthy et al. (2001), the nature of the performing arts makes them particularly susceptible to time constraints, as they require extensive planning and dedication. In this analysis, a control for marital status and for the number of minors living at home is added.

Another variable describing the available resources for participation is individual health status (*Di*), which is considered here as a binary variable that determines whether an individual has some form of disability. This fact can negatively influence physical participation, but *ceteris paribus* could positively influence digital visits, if there were a trade-off between the two. The inclusion of this variable allows us to isolate further the effect of decaying health capital with age, from pure age of life-cycle effects (Seaman, 2005). Surprisingly, health status has very rarely been considered an important individual resource for cultural participation. Kaimal et al. (2016) demonstrate, using our same source of data, that the increase in digital media by art therapists is one of the best practices for the use of digital media. Bille (2010) controls for disability (restricted mobility) in the estimation of the determinants of leisure and cultural engagement in Denmark. The author finds statistically significant effects only in some of the leisure alternatives, out of the 35 considered, and it is not possible to infer a clear pattern from the results. The impact of health status has also been considered in sports participation and active engagement (as in Muñiz et al., 2014), and the impact of cultural participation on health and individual well-being has been explored (Galloway, 2006). At the same time, physical difficulties are among the most important reasons old people do not become digitally engaged (Pew Research Center, 2014). An indicator variable (*Disa*) for those individuals with any one or more of the following health complaints is constructed: deaf or serious hearing difficulties, visually impaired or sight problems even with glasses, a serious mental, physical or emotional condition, difficulty walking or climbing stairs, difficulty dressing or bathing, or difficulty doing errands without assistance.

Regarding the geographical variables (*Geo*), it is considered whether the individual lives in a city, a town or in a metropolis or non-metropolitan area. This is because location is not relevant for digital access, but it is important for actual visits. Living far from a museum directly influences availability by increasing the time needed to attend, and habitat may therefore have a negative impact on physical participation.

Table 2 Descriptive statistics

Variable	Type	Obs	Mean	Std. Dev	Min	Max
Musego	D	12,130	0.227	–	0	1
Handheld	D	9249	0.079	–	0	1
Internet	D	9198	0.044	–	0	1
Musehand	C	37,266	0.062	0.354	0	3
Museint	C	37,266	0.058	0.336	0	3
Age1 (18–24)	D	37,266	0.084	–	0	1
Age2 (25–34)	D	37,266	0.165	–	0	1
Age3 (35–44)	D	37,266	0.170	–	0	1
Age4 (45–54)	D	37,266	0.188	–	0	1
Age5 (55–64)	D	37,266	0.182	–	0	1
Age6 (65 +)	D	37,266	0.211	–	0	1
Male	D	37,266	0.471	–	0	1
Female	D	37,266	0.529	–	0	1
White	D	37,266	0.839	–	0	1
Black	D	37,266	0.088	–	0	1
Otherrace	D	37,266	0.073	–	0	1
Edu (associate/university degree)	D	37,266	0.403	–	0	1
Children_arts_school	D	9253	0.100	–	0	1
Employ (employed)	D	37,266	0.609	–	0	1
Unemp (unemployed)	D	37,266	0.047	–	0	1
Notforce (not in the labor force)	D	37,266	0.343	–	0	1
Management, business, and financial operations occupations	D	37,266	0.111	–	0	1
Professional and related occupations	D	37,266	0.150	–	0	1
Service occupations	D	37,266	0.114	–	0	1
Sales and related occupations	D	37,266	0.065	–	0	1
Office and administrative support occupations	D	37,266	0.083	–	0	1
Farming, fishing, and forestry occupations	D	37,266	0.006	–	0	1
Construction and extraction occupations	D	37,266	0.034	–	0	1
Installation, maintenance, and repair occupations	D	37,266	0.023	–	0	1
Production occupations	D	37,266	0.040	–	0	1
Transportation and material moving occupations	D	37,266	0.039	–	0	1
Hinc1 (less than 25.000 USD)	D	37,266	0.222	–	0	1
Hinc2 (25,000 to 49,000 USD)	D	37,266	0.260	–	0	1
Hinc3 (50,000 to 99,999 USD)	D	37,266	0.317	–	0	1
Hinc4 (more than 100,000 USD)	D	37,266	0.201	–	0	1
Married	D	37,266	0.578	–	0	1
Widowed	D	37,266	0.066	–	0	1
Single	D	37,266	0.219	–	0	1
Divorced	D	37,266	0.137	–	0	1
No children < 18 at home	D	37,266	0.716	–	0	1
Child1 (1 child < 18 at home)	D	37,266	0.117	–	0	1
Child2 (2 children < 18)	D	37,266	0.108	–	0	1

Table 2 (continued)

Variable	Type	Obs	Mean	Std. Dev	Min	Max
Child3plus (more than 3 children < 18)	D	37,266	0.059	–	0	1
Disa	D	37,266	0.128	–	0	1
Central	D	37,266	0.224	–	0	1
Balance	D	37,266	0.372	–	0	1
Nometro	D	37,266	0.216	–	0	1
Others	D	37,266	0.188	–	0	1
Internet_use	C	6392	1.689	1.092	1	6

Online consumption is explained by the same set of variables with the exception of *internet_use* that highlights how often a person uses the internet; the variable is categorical from 1 to 6 where 1 indicates several times a day; 2 indicates about once a day; 3 is from 3 to 5 times a week; 4 is for 1 or 2 times a week; 5 is every few weeks; and 6 is less often than 5. We believe that the use of internet has an impact on the cultural consumption through internet or mobile devices, whilst the use of internet has no impact on the cultural consumption onsite (*musego*). In Eq. (1), we have included (and hence excluded from Eq. (2)) the variable, *Nchild,* which identifies the number of children under 18 in the family. This variable is included in the cultural participation model due to the time constraint restriction that does not occur in the case of online consumption.

Following Prieto-Rodríguez and Fernández-Blanco (2000), it is expected that some variables exert a similar effect, particularly those that shape the individual taste for visual arts and the common cultural capital needed to appreciate and transform cultural goods (museum visits or visual electronic and digital content, respectively) into meaningful cultural experiences. It is also expected that the variables that relate to the different production function and resources will have a different effect in each equation in the bivariate model.

The descriptive statistics of the dependent and independent variables are presented in Table 2. In our sample, 23% of the 12,130 respondents declared they had visited a museum during the previous year (*musego*). For the electronic and digital consumption of visual arts, the sample size shrinks to about 9000 respondents due to the survey's module structure. 51.3% of the sample respondents used handheld and mobile devices, with 7.9% of them using handheld or mobile devices for the visual arts (*handheld variable*). For the use of the internet, 69.3% reported using it, of which 4.4% used it to access the visual arts (*internet* variable). Due to the aforementioned structure of the 2012 SPPA, when the information from different modules is combined, the sample is reduced to 1603 observations for estimating the model that considers access through handheld and mobile devices and internet access.[1]

[1] Summary statistics of the reduced sample are available from the authors upon request.

4 Results and discussion

4.1 Multinomial logit model

Table 3 shows the estimated coefficient results for the average museum attendance and handheld or mobile consumption of visual arts content (Model 1) and the average museum attendance and internet consumption (Model 2), respectively. Table 4 shows the marginal effects of both models. The models are estimated using a multinomial logit methodology. In this case, the dependent variable takes a value from 0 to 3; 0 if the person did not attend any activities; 1 if the person attended both; 2 if the person attended only *musego*; and 3 if the person attended only *handheld/internet.* In particular, the first column of each model shows the impact of each variable on the probability to attend both types of event (online and onsite), whilst the second and third columns show the impact on the probability of attending onsite (*musego*) and online (*handheld* in Model 1 and *internet* in Model 2), respectively.

As previously indicated in the empirical specification of the model, the explanatory variables are chosen to test the hypotheses derived from the theoretical models presented: demographic variables, educational/cultural variables, occupational status, household variables (household income and variables linked to the availability of time), health status, and geographical localisation.

Starting with the demographic variables, contrary to other studies (De la Vega et al., 2020; Montoro-Pons and Cuadrado-García 2011), our results do not show any statistically significant impact of age, with the only exception of the internet consumption, where, as expected, the probability to attend decreases with age, compared with the baseline category of younger people (18–24 years). In fact, whilst the *age2* category (25–34 years) shows a marginal effect of 0.111 compared with the baseline category, the *age6* group (65 +) shows an impact of 0.098 (Table 4). These results highlight the complexity of the role of age in cultural participation, and especially the different role that it can play in onsite and online participation. The age as a continuous variable (*age* and *age squared*) is also added in our estimation, but no statistically significant effect is displayed.[2] On the other hand, females show a higher probability of attending museums than males only in the onsite participation (*musego*), which is consistent with previous research. This impact presents a marginal effect of 0.046 in Model 1 and 0.061 in the case of Model 2. Significant gender differences are found in the cultural participation literature (see Ateca-Amestoy, 2008; Bihagen & Katz-Gerro, 2000; Castiglione, 2017; Mauri & Wolf, 2021; and Suárez-Fernández & Boto-García, 2019), demonstrating that men and women typically enjoy different amounts of time for leisure (Mattingly & Bianchi, 2003) and display different preferences for culture (Christin, 2012). Females prefer highbrow cultural activities, whilst males engage more in popular ones (Bihagen & Katz-Gerro, 2000). Moreover, as in De la Vega et al. (2020) no gender differences are found in online consumption, both *handheld* and *internet*. In addition, our results

[2] These results are available upon request from the authors.

Table 3 Multilogit model estimates for museum visits, handheld and internet participation. Coefficients

Variables	Model 1			Model 2		
	Both	Musego	Handheld	Both	Musego	Internet
Reference group: age1 (18–24)						
Age2 (25–34)	− 0.0609	− 0.363	0.988	− 0.0538	− 0.293	16.49***
	(0.449)	(0.346)	(0.876)	(0.698)	(0.300)	(0.750)
Age3 (35–44)	− 0.340	− 0.392	0.233	− 0.447	− 0.399	15.14***
	(0.544)	(0.371)	(0.915)	(0.760)	(0.343)	(1.125)
Age4 (45–54)	− 0.510	−0.231	0.0464	− 0.217	− 0.331	16.14***
	(0.589)	(0.375)	(1.022)	(0.803)	(0.353)	(0.834)
Age5 (55–64)	− 0.113	0.516	− 0.264	0.588	0.272	15.36***
	(0.559)	(0.387)	(1.030)	(0.833)	(0.350)	(1.447)
Age6 (65 +)	− 0.824	0.642	0.167	0.347	0.314	14.57***
	(0.885)	(0.426)	(0.887)	(0.985)	(0.397)	(1.658)
Reference group: male						
Female	0.413	0.547***	− 0.352	0.200	0.612***	− 0.993
	(0.284)	(0.200)	(0.413)	(0.383)	(0.185)	(0.728)
Reference group: white						
Black	− 0.363	− 1.054**	0.697	0.0121	− 1.067***	0.989
	(0.546)	(0.436)	(0.549)	(0.716)	(0.396)	(0.883)
Otherrace	− 0.422	0.101	0.00358	− 0.503	0.0472	0.700
	(0.510)	(0.291)	(0.622)	(0.738)	(0.277)	(0.967)
Edu (associate/university degree)	1.322***	0.544***	− 0.260	1.506***	0.648***	0.969
	(0.347)	(0.193)	(0.413)	(0.455)	(0.184)	(0.695)
Children_arts_school	1.718***	0.662**	0.683	1.819***	0.736**	1.262
	(0.364)	(0.304)	(0.548)	(0.390)	(0.291)	(1.030)
Reference group: employ (employed)						
Unemp (unemployed)	− 0.532	0.411	0.456	0.380	0.116	1.665
	(0.785)	(0.370)	(0.805)	(0.802)	(0.382)	(1.426)

Table 3 (continued)

Variables	Model 1			Model 2		
	Both	Musego	Handheld	Both	Musego	Internet
Notforce (not in the labor force)	− 0.750	0.0150	0.312	− 0.635	− 0.0983	0.240
	(0.528)	(0.304)	(0.575)	(0.630)	(0.288)	(0.871)
Reference group: Office and administrative support occupations						
Management, business, and financial operations occupations	− 0.220	− 0.0451	0.426	− 0.605	− 0.0248	− 17.49***
	(0.468)	(0.360)	(0.683)	(0.731)	(0.327)	(0.693)
Professional and related occupations	0.191	0.306	− 0.380	0.337	0.207	− 2.887***
	(0.381)	(0.327)	(0.703)	(0.572)	(0.294)	(1.090)
Service occupations	− 0.220	− 0.275	− 1.676	0.452	− 0.439	− 0.651
	(0.520)	(0.360)	(1.160)	(0.643)	(0.340)	(0.979)
Sales and related occupations	0.395	0.200	− 0.0833	0.172	0.262	− 16.52***
	(0.508)	(0.376)	(0.729)	(0.788)	(0.346)	(0.776)
Farming, fishing, and forestry occupations	− 12.73***	− 13.45***	− 14.40***	− 15.41***	− 15.99***	− 16.47***
	(0.741)	(0.554)	(0.856)	(0.899)	(0.542)	(1.639)
Construction and extraction occupations	− 0.532	− 1.067	− 0.0598	− 15.83***	− 0.652	− 17.63***
	(1.120)	(1.070)	(0.910)	(0.677)	(0.805)	(1.122)
Installation, maintenance, and repair occupations	− 13.53***	0.494	− 0.230	− 16.13***	0.312	− 17.63***
	(0.440)	(0.594)	(1.208)	(0.677)	(0.583)	(0.754)
Production occupations	− 0.0627	0.00557	− 13.98***	0.478	− 0.0407	0.0906
	(1.133)	(0.567)	(0.638)	(1.251)	(0.562)	(1.322)
Transportation and material moving occupations	− 0.528	− 0.705	− 14.26***	− 16.09***	− 0.429	− 17.27***
	(1.097)	(0.772)	(0.613)	(0.647)	(0.641)	(1.053)
Reference group: hinc1 (less than 25.000 USD						
Hinc2 (25,000 to 49,000 USD)	− 0.270	− 0.215	0.185	0.450	− 0.314	1.493
	(0.452)	(0.286)	(0.638)	(0.661)	(0.264)	(0.964)
Hinc3 (50,000 to 99,999 USD)	− 0.268	0.199	0.780	0.312	0.0210	1.552
	(0.435)	(0.268)	(0.631)	(0.696)	(0.248)	(1.098)

Table 3 (continued)

Variables	Model 1			Model 2		
	Both	Musego	Handheld	Both	Musego	Internet
Hinc4 (more than 100,000 USD)	0.155	0.736**	0.406	0.648	0.553**	1.773
	(0.471)	(0.304)	(0.706)	(0.749)	(0.281)	(1.254)
Reference group: married						
Widowed	0.501	0.0968	0.358	− 0.683	0.190	− 15.30***
	(0.777)	(0.407)	(0.781)	(1.281)	(0.395)	(1.113)
Single	0.457	0.525**	− 0.474	0.822	0.430*	− 0.437
	(0.393)	(0.268)	(0.519)	(0.593)	(0.243)	(0.963)
Divorced	− 1.113*	0.406*	0.311	− 0.358	0.181	− 0.0541
	(0.592)	(0.244)	(0.512)	(0.577)	(0.238)	(0.956)
Reference group: no children < 18 at home						
Child1 (1 child < 18 at home)	− 1.406***	0.0783	0.104	− 0.597	− 0.270	− 0.531
	(0.515)	(0.322)	(0.554)	(0.547)	(0.315)	(1.173)
Child2 (2 children < 18)	− 1.167***	− 0.743*	0.0376	− 0.676	− 0.883**	− 0.860
	(0.450)	− 0.442	(0.530)	(0.544)	(0.425)	(0.986)
Child3plus (more than 3 children < 18)	− 1.695**	0.435	− 0.0547	− 1.788*	0.0850	− 1.654
	(0.799)	− 0.399	(0.761)	(1.049)	(0.388)	(1.154)
Disa	0.147	− 0.0287	− 0.417	1.019*	− 0.147	1.032
	(0.597)	(0.306)	(0.678)	(0.597)	(0.309)	(0.778)
Reference group: central						
Balance	− 0.340	− 0.397*	0.161	0.546	− 0.616***	−0.0613
	(0.321)	(0.204)	(0.429)	(0.432)	(0.194)	(0.710)
Nometro	− 0.484	− 1.004***	− 0.844	− 0.223	− 0.983***	− 0.748
	(0.452)	(0.319)	(0.709)	(0.692)	(0.290)	(1.083)
Others	− 0.131	− 0.392	− 0.282	− 0.0847	− 0.370	0.810
	(0.362)	(0.258)	(0.572)	(0.615)	(0.232)	(0.703)

Table 3 (continued)

Variables	Model 1			Model 2		
	Both	Musego	Handheld	Both	Musego	Internet
Internet_use	− 0.586**	0.0994	− 0.352	− 0.848**	0.0700	− 1.054
	(0.250)	(0.0808)	(0.275)	(0.414)	(0.0793)	(0.902)
Constant	− 2.430***	− 3.026***	− 3.555***	− 4.395***	− 2.405***	− 19.68***
	(0.753)	(0.543)	(1.317)	(1.183)	(0.485)	(1.743)
Observations	1603	1603	1603	1603	1603	1603

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 4 Multilogit model estimates for museum visits, handheld and internet participation. ME

Variables	Model 1			Model 2		
	Both	Musego	Handheld	Both	Musego	Internet
Reference group: age1 (18–24)						
Age2 (25–34)	− 0.013	− 0.033	0.021	− 0.005	− 0.041	0.111***
	(0.017)	(0.300)	(0.018)	(0.016)	(0.030)	(0.041)
Age3 (35–44)	− 0.011	− 0.328	0.006	− 0.014	− 0.049	0.102***
	(0.021)	(0.032)	(0.018)	(0.018)	(0.034)	(0.038)
Age4 (45–54)	− 0.018	− 0.017	0.002	− 0.009	− 0.044	0.109***
	(0.023)	(0.033)	(0.021)	(0.019)	(0.035)	(0.039)
Age5 (55–64)	− 0.007	0.046	− 0.006	0.008	0.013	0.103***
	(0.022)	(0.034)	(0.021)	(0.019)	(0.035)	(0.040)
Age6 (65+)	− 0.036	0.060	0.00358	0.002	0.019	0.098***
	(0.034)	(0.037)	(0.019)	(0.023)	(0.040)	(0.037)
Reference group: male						
Female	0.013	0.046***	− 0.009	0.003	0.061***	− 0.007
	(0.011)	(0.017)	(0.008)	(0.009)	(0.018)	(0.005)
Reference group: white						
Black	− 0.009	− 0.092***	0.017	0.004	− 0.107***	0.007
	(0.021)	(0.038)	(0.011)	(0.016)	(0.039)	(0.006)
Otherrace	− 0.017	0.011	0.0002	− 0.012	0.006	0.005
	(0.020)	(0.025)	(0.013)	(0.018)	(0.027)	(0.007)
Edu (associate/university degree)	0.048***	0.041***	− 0.008	0.032***	0.058***	0.006
	(0.014)	(0.017)	(0.008)	(0.011)	(0.018)	(0.005)
Children_arts_school	0.062***	0.047	0.011	0.065**	0.736**	0.007
	(0.015)	(0.026)	(0.011)	(0.028)	(0.291)	(0.007)

Table 4 (continued)

Variables	Model 1			Model 2		
	Both	Musego	Handheld	Both	Musego	Internet
Reference group: employ (employed)						
Unemp (unemployed)	− 0.023	0.038	0.009	0.008	0.009	0.011
	(0.030)	(0.032)	(0.017)	(0.019)	(0.038)	(0.010)
Notforce (not in the labor force)	− 0.029	0.005	0.007	− 0.015	− 0.007	0.002
	(0.030)	(0.026)	(0.012)	(0.015)	(0.029)	(0.006)
Reference group: Office and administrative support occupations						
Management, business, and financial operations occupations	− 0.009	− 0.004	0.009	− 0.009	0.013	− 0.118***
	(0.018)	(0.031)	(0.014)	(0.016)	(0.032)	(0.041)
Professional and related occupations	0.006	0.026	− 0.008	0.008	0.021	− 0.020**
	(0.015)	(0.028)	(0.014)	(0.013)	(0.029)	(0.010)
Service occupations	− 0.005	− 0.019	− 0.033	0.013	− 0.045	− 0.004
	(0.020)	(0.013)	(0.024)	(0.015)	(0.034)	(0.007)
Sales and related occupations	0.014	0.015	− 0.002	0.008	0.004	− 0.112***
	(0.019)	(0.033)	(0.015)	(0.018)	(0.034)	(0.040)
Farming, fishing, and forestry occupations	− 0.405***	− 1.075***	− 0.252***	− 0.292***	− 1.515***	− 0.094***
	(0.057)	(0.088)	(0.047)	(0.052)	(0.107)	(0.036)
Construction and extraction occupations	− 0.015	− 0.090	0.001	− 0.362***	0.011	− 0.113***
	(0.043)	(0.093)	(0.018)	(0.057)	(0.080)	(0.041)
Installation, maintenance, and repair occupations	− 0.525***	0.118**	0.007	− 0.373***	0.108*	− 0.114***
	(0.061)	(0.052)	(0.025)	(0.058)	(0.058)	(0.040)
Production occupations	0.010	0.030	− 0.283***	0.011	− 0.006	0.0004
	(0.044)	(0.049)	(0.050)	(0.029)	(0.056)	(0.009)

Table 4 (continued)

Variables	Model 1			Model 2		
	Both	Musego	Handheld	Both	Musego	Internet
Transportation and material moving occupations	− 0.003	− 0.029	− 0.286***	− 0.369***	0.034	− 0.111***
	(0.042)	(0.067)	(0.051)	(0.057)	(0.064)	(0.040)
Reference group: hinc1 (less than 25.000 USD						
Hinc2 (25,000 to 49,000 USD)	− 0.009	− 0.018	0.004	0.011	− 0.034	0.010
	(0.017)	(0.025)	(0.013)	(0.015)	(0.026)	(0.007)
Hinc3 (50,000 to 99,999 USD)	− 0.012	0.017	0.016	0.007	− 0.0003	0.010
	(0.017)	(0.023)	(0.013)	(0.016)	(0.025)	(0.008)
Hinc4 (more than 100,000 USD)	0.002	0.063***	0.007	0.012	0.051*	0.011
	(0.018)	(0.027)	(0.014)	(0.017)	(0.028)	(0.009)
Reference group: married						
Widowed	0.018	0.005	0.007	− 0.012	0.033	− 0.103***
	(0.030)	(0.035)	(0.016)	(0.029)	(0.040)	(0.037)
Single	0.015	0.044**	− 0.011	0.018	0.040*	− 0.004
	(0.015)	(0.023)	(0.011)	(0.014)	(0.024)	(0.006)
Divorced	− 0.046**	0.041*	0.006	− 0.009	0.019	− 0.004
	(0.023)	(0.021)	(0.010)	(0.013)	(0.024)	(0.006)
Reference group: no children < 18 at home						
Child1 (1 child < 18 at home)	− 0.055***	0.014	0.003	− 0.013	− 0.024	− 0.003
	(0.021)	(0.028)	(0.011)	(0.013)	(0.031)	(0.008)
Child2 (2 children < 18)	− 0.041**	− 0.059*	0.003	− 0.012	− 0.085**	− 0.004
	(0.018)	− 0.042	(0.011)	(0.03)	(0.042)	(0.006)
Child3plus (more than 3 children < 18)	− 0.067**	0.048	− 0.0001	− 0.037	0.028	− 0.111***
	(0.031)	(− 0.034)	(0.015)	(0.025)	(0.038)	(0.039)

Table 4 (continued)

Variables	Model 1			Model 2		
	Both	Musego	Handheld	Both	Musego	Internet
Disa	0.006	− 0.002	− 0.009	0.024*	− 0.019	0.007
	(0.023)	(0.027)	(0.014)	(0.014)	(0.031)	(0.005)
Reference group: central						
Balance	− 0.011	− 0.033*	0.004	0.015	− 0.063***	− 0.0001
	(0.012)	(0.018)	(0.009)	(0.010)	(0.019)	(0.005)
Nometro	− 0.012	− 0.083***	− 0.015	− 0.001	− 0.096***	− 0.004
	(0.017)	(0.028)	(0.014)	(0.016)	(0.029)	(0.007)
Others	− 0.003	− 0.033*	− 0.005	− 0.001	− 0.037*	0.006
	(0.014)	(0.022)	(0.012)	(0.014)	(0.023)	(0.005)
Internet_use	− 0.022**	0.013*	− 0.007	− 0.020**	0.011	− 0.007
	(0.010)	(0.007)	(0.007)	(0.020)	(0.008)	(0.007)
Observations	1603	1603	1603	1603	1603	1603

See Table 3

show a lower probability of attending onsite museums or art galleries for black people compared with white.

The effect of having completed higher education (university degree or above) is positive, as expected, and statistically significant in all the estimated models with a marginal effect of about 0.04 (with the only exception of online participation). This result is in line with the onsite cultural participation literature (see Seaman, 2005) and with those of De la Vega et al. (2020) and Montoro-Pons and Cuadrado-García (2011) which find a positive impact only for live participation. The relationship between education on cultural participation is well known in the literature and is related to the fact that the enjoyment of the highbrow arts relies on the sensitiveness of the perceiver (Castiglione, 2017), since to grasp the full meaning of a cultural event, interpretation skills and shared cultural capital are needed. This result is also supported by the strong significance that having children at school that attend some form of arts strongly increases the parent's probability of consuming *both* (onsite and online) and *musego*.

Our models also considered the labour status and occupation of the individual if employed. Taking as the baseline to be employed at an *office or administrative support occupation*, for both visits to museums and online participation (*handheld* and *internet*), there is a strong negative effect of belonging to *farming, fishing, and forestry occupations*. This is not a very surprising result since people working in this category are not directly related to cultural capital or with the use of personal devices or internet connections for their occupation. Working on *installation, maintenance, and repair occupations* increases the probability to attend onsite (*musego*) by around 0.1, whilst it strongly decreases the probability to attend both (the marginal effect is around −0.4) compared with the baseline category. On the other hand, the handheld participation has a lower probability to be attended by people working in *transportation and material moving occupations*. However, internet participation is lower for people working in all the sectors with the exception of *service occupations* and *production occupations*. The different impact on cultural participation with respect to the occupational sector is found by other scholars (see for example Ateca-Amestoy, 2008; De la Vega et al., 2020).

The aforementioned results refer to variables that influence an individual's cultural capital and preferences. Variables related to the household's status are also considered. However, we do not find a strong impact for the income categories in either of the models.

For household composition variables, and with respect to being married, a positive effect for being single is found. The impact of the presence of two children under 18 decreases the probability of museum-going. Whilst having three or more children decreases the probability to attend both types of events, it does not show any impact on the probability to attend only onsite or online. These results are in line with previous results given that attending any leisure activity is not feasible without substantial extra child-minding costs and indeed psychological costs in being separated from one's children, especially given the limited time people have nowadays to be with their offspring (Castiglione, 2017; Seaman, 2005).

Our results do not suggest a strong relationship between people with a sensory, motor, or mental disability and a higher probability of consuming visual arts through the *internet* or *handheld*, or both. The marginal effect is positive only in Model 2 and on attending both types of events. This result is new in the literature since the importance of online arts consumption for people with disabilities is a new research field.

Our estimated results seem to confirm the typical urban characteristic of museum-going; with respect to living in a central area, all the other types of habitat exert a negative effect over the probability of visiting museums and art galleries (*musego*). Living in a *balance*, a *non-metropolitan* and *other areas,* decreases the probability of onsite attendance by around 0.006. This finding is similar to that of Ateca-Amestoy (2008). Finally, the use of internet shows a negative impact on the probability of attending both types of events by around 0.020.

We have also two different versions of our model (A and B). In model A, the variable *Nchild*, which indicates the number of children under 18 in the family, instead of the 3 dummy variables for the 4 categories, is included. Models 1 and 2 are estimated without the variable *internet_use*, which indicates how often a person uses the internet. In both cases, the results of other variables are similar to those presented in Table 3, indicating the robustness of our model.[3]

4.2 Recursive bivariate probit model

In order to explore the nature (complementarity or substitutability) of the two ways (*musego* and *handheld/internet*) to consume visual arts, we estimate a seemingly unrelated recursive bivariate probit model. In particular, the specifications take into account both visits to museums and art galleries and participation through handheld or mobile devices (*musego-handheld – Model 1*), and visits to museums and art galleries and participation through internet (*musego-internet – Model 2*). The SUR-Biprobit model provides for the inclusion of an endogenous variable in the right-hand side of one equation. Both models are estimated using the maximum likelihood (MLE) procedure. However, even though in this model an explanatory endogenous variable is used, the endogeneity problem can be ignored in formulating the log-likelihood function (Greene, 2007) since the minimum restriction that guarantees the model is identified and MLE yields consistent estimates (Montoro-Pons and Cuadrado-García 2011).

Results are reported in Tables 5 and 6. The tables also include the estimated correlation coefficient, ρ, and a joint significant test, χ^2, together with the Akaike's information criterion (AIC) and Bayesian information criterion (BIC). All tests are statistically different from zero justifying our decision to jointly explain both decisions, as they are interdependent (with the only exception of Model 1 (*musego* and *handheld*).

In Table 5, the handheld's impact over physical participation is taken into account, (Model 1A) followed by the impact that visits have over handheld access (Model 1B). The table presents both the coefficients (first two columns of each

[3] Those results are available upon request from the author.

Table 5 Seemingly unrelated bivariate probit model estimates for museum visits and handheld

Variables	Model 1A—Coefficients		Model 1A—Marginal Effects			
	Musego	Handheld	Pr(mus=1,hand=1)	Pr(mus=1,hand=0)	Pr(mus=0,hand=1)	Pr(mus=0,hand=0)
Handheld	1.342		0.043***	0.299	−0.043***	−0.299
	(1.305)		(0.012)	(0.280)	(0.012)	(0.280)
Musego						
Reference group: age1 (18-24)						
Age2 (25–34)	−0.317	0.209	0.001	−0.082	0.038	0.043
	(0.230)	(0.246)	(0.015)	(0.053)	(0.034)	(0.059)
Age3 (35–44)	−0.0729	−0.0672	−0.006	−0.013	−0.007	0.025
	(0.252)	(0.284)	(0.019)	(0.059)	(0.038)	(0.067)
Age4 (45–54)	0.0773	−0.290	−0.013	0.033	−0.041	0.021
	(0.269)	(0.321)	(0.023)	(0.061)	(0.042)	(0.073)
Age5 (55–64)	0.390	−0.0130	0.012	0.088	−0.014	−0.085
	(0.265)	(0.299)	(0.018)	(0.063)	(0.045)	(0.067)
Age6 (65+)	0.396	0.0334	0.015	0.086	−0.008	−0.093
	(0.308)	(0.361)	(0.011)	(0.063)	(0.055)	(0.081)
Reference group: male						
Female	0.357***	−0.0231	0.010	0.081***	−0.015	−0.076**
	(0.136)	(0.157)	(0.012)	(0.033)	(0.024)	(0.034)
Reference group: white						
Black	−0.648***	0.0979	−0.015	−0.150***	0.034	0.131**
	(0.243)	(0.276)	(0.019)	(0.061)	(0.044)	(0.061)
Otherrace	−0.210	0.156	0.002	−0.055	0.027	0.026
	(0.226)	(0.258)	(0.015)	(0.056)	(0.037)	(0.054)
Edu (Associate/university degree)	0.492***	0.344**	0.035	0.091**	0.029	−0.155***
	(0.188)	(0.173)	(0.026)	(0.040)	(0.039)	(0.040)

Table 5 (continued)

Variables	Model 1A—Coefficients		Model 1A—Marginal Effects			
	Musego	Handheld	Pr(mus=1,hand=1)	Pr(mus=1,hand=0)	Pr(mus=0,hand=1)	Pr(mus=0,hand=0)
Children_arts_school	0.547**	0.517**	−0.011	0.094*	0.051	−0.191***
	(0.275)	(0.211)	(0.018)	(0.054)	(0.036)	(0.063)
Reference group: employ (employed)						
Unemp (unemployed)	0.151	−0.292	−0.011	0.050	−0.044	0.005
	(0.290)	(0.345)	(0.018)	(0.072)	(0.051)	(0.068)
Notforce (not in the labor force)	−0.151	−0.398*	−0.026	−0.012	−0.048	0.086
	(0.246)	(0.239)	(0.023)	(0.057)	(0.038)	(0.038)
Reference group: Office and administrative support occupations						
Management, business, and financial operations occupations	−0.260	−0.0252	−0.010	−0.057	0.005	0.062
	(0.270)	(0.281)	(0.019)	(0.066)	(0.039)	(0.064)
Professional and related occupations	0.0154	−0.0113	−0.0001	0.004	−0.002	−0.002
	(0.251)	(0.248)	(0.014)	(0.061)	(0.036)	(0.057)
Service occupations	−0.0773	−0.527	−0.031	0.011	−0.067*	0.087
	(0.291)	(0.323)	(0.035)	(0.061)	(0.039)	(0.074)
Sales and related occupations	0.147	0.0870	0.010	0.028	0.007	−0.044
	(0.303)	(0.312)	(0.018)	(0.073)	(0.046)	(0.071)
Farming, fishing, and forestry occupations	−5.559***	−5.877***	−0.499*	−0.919***	−0.602**	2.020***
	(0.310)	(0.419)	(0.317)	(0.174)	(0.308)	(0.173)

Table 5 (continued)

Variables	Model 1A—Coefficients		Model 1A—Marginal Effects			
	Musego	Handheld	Pr(mus=1,hand=1)	Pr(mus=1,hand=0)	Pr(mus=0,hand=1)	Pr(mus=0,hand=0)
Constructions and extraction occupations	−0.226	−0.0125	−0.008	−0.050	0.006	0.052
	(0.627)	(0.460)	(0.027)	(0.149)	(0.070)	(0.133)
Installation, maintenance, and repair occupations	−0.220	−0.693	−0.045	−0.011	−0.085	0.141
	(0.455)	(0.525)	(0.038)	(0.112)	(0.085)	(0.095)
Production occupations	−0.167	−1.304***	−0.076	0.034	−0.168**	0.210**
	(0.408)	(0.483)	(0.048)	(0.091)	(0.081)	(0.106)
Transportation and material moving occupations	−0.113	−0.692	−0.041	0.012	−0.088	0.117
	(0.480)	(0.626)	(0.057)	(0.103)	(0.030)	(0.140)
Reference group: hinc1 (less than 25.000 USD)						
Hinc2 (25,000 to 49,000 USD)	0.0642	−0.0365	0.0001	0.016	−0.007	−0.009
	(0.185)	(0.224)	(0.014)	(0.043)	(0.030)	(0.052)
Hinc3 (50,000 to 99,999 USD)	0.179	0.106	0.012	0.034	0.008	−0.054
	(0.177)	(0.227)	(0.018)	(0.041)	(0.030)	(0.050)
Hinc4 (more than 100,000 USD)	0.516**	0.208	0.028	0.103**	0.011	−0.143**
	(0.236)	(0.259)	(0.032)	(0.051)	(0.033)	(0.067)
Reference group: married						
Widowed	−0.177	−0.00541	−0.006	−0.039	0.005	0.040
	(0.321)	(0.382)	(0.022)	(0.076)	(0.054)	(0.085)
Single	0.436*	0.270	0.029	0.082	0.022	0.133***
	(0.244)	(0.189)	(0.023)	(0.054)	(0.040)	(0.051)

Table 5 (continued)

Variables	Model 1A—Coefficients		Model 1A—Marginal Effects			
	Musego	Handheld	Pr(mus=1,hand=1)	Pr(mus=1,hand=0)	Pr(mus=0,hand=1)	Pr(mus=0,hand=0)
Divorced	0.117	−0.139	−0.004	0.0234	−0.022	−0.008
	(0.178)	(0.224)	(0.012)	(0.044)	(0.032)	(0.045)
Nchild	−0.160*		−0.005	−0.036*	0.005	0.036*
	(0.0977)		(0.022)	(0.021)	(0.005)	(0.022)
Disa	0.0751	−0.0647	−0.001	0.020	−0.011	−0.008
	(0.202)	(0.263)	(0.016)	(0.046)	(0.036)	(0.059)
Reference group: central						
Balance	−0.267*	−0.103	−0.014	−0.054	−0.005	0.073**
	(0.152)	(0.168)	(0.014)	(0.035)	(0.005)	(0.037)
Nometro	−0.415*	−0.0514	−0.016	−0.090*	0.007	0.099*
	(0.222)	(0.255)	(0.022)	(0.052)	(0.036)	(0.060)
Others	−0.229	−0.184	−0.017	−0.041	−0.017	0.075
	(0.193)	(0.223)	(0.021)	(0.041)	(0.030)	(0.0354)
Internet_use		−0.217**	−0.012	0.011	−0.029**	0.029**
		(0.0977)	(0.008)	(0.008)	(0.014)	(0.014)
ρ		−0.206				
		(0.783)				
c^2		3056,15				
		(0.000)				
Log likelihood		−6685953,4				
AIC		13400000				
BIC		13400000				
Constant	−1.291***	−0.959**				
	(0.393)	(0.438)				
Observations	812	812	812	812	812	812

Table 5 (continued)

Variables	Model 1B—Coefficients		Model 1B—Marginal Effects			
	Musego	Handheld	Pr(mus=1,hand=1)	Pr(mus=1,hand=0)	Pr(mus=0,hand=1)	Pr(mus=0,hand=0)
Handheld						
Musego		2.274***	0.114***	−0.114***	0.260***	−0.260***
		(0.387)	(0.044)	(0.044)	(0.017)	(0.017)
Reference group: age1 (18−24)						
Age2 (25–34)	−0.152	0.326	−0.007	−0.050	0.047	−0.036
	(0.210)	(0.219)	(0.014)	(0.051)	(0.031)	(0.043)
Age3 (35–44)	−0.119	−0.0133	−0.008	−0.025	0.005	0.028
	(0.233)	(0.252)	(0.014)	(0.058)	(0.037)	(0.047)
Age4 (45–54)	−0.0526	−0.319	−0.019	0.004	−0.033	0.048
	(0.251)	(0.279)	(0.15)	(0.062)	(0.042)	(0.055)
Age5 (55–64)	0.278	−0.395	−0.004	0.081	−0.061*	−0.016
	(0.241)	(0.254)	(0.014)	(0.060)	(0.037)	(0.047)
Age6 (65+)	0.270	−0.366	−0.003	0.078	−0.057	−0.0918
	(0.277)	(0.297)	(0.014)	(0.069)	(0.044)	(0.056)
Reference group: male						
Female	0.327**	−0.283*	0.005	0.087***	−0.051**	−0.040
	(0.129)	(0.160)	(0.008)	(0.031)	(0.022)	(0.027)
Reference group: white						

Table 5 (continued)

Variables	Model 1B—Coefficients		Model 1B—Marginal Effects			
	Musego	Handheld	Pr(mus=1,hand=1)	Pr(mus=1,hand=0)	Pr(mus=0,hand=1)	Pr(mus=0,hand=0)
Black	−0.670***	0.527**	−0.012	−0.175***	0.099***	0.088**
	(0.217)	(0.238)	(0.014)	(0.053)	(0.034)	(0.046)
Otherrace	−0.234	0.219	−0.002	−0.063	0.038	0.027
	(0.219)	(0.261)	(0.012)	(0.057)	(0.038)	(0.041)
Edu (associate/university degree)	0.616***	−0.140	0.029***	0.144***	−0.051*	−0.120***
	(0.134)	(0.196)	(0.008)	(0.032)	(0.029)	(0.037)
Children_arts_school	0.835***	0.111	0.054	0.179***	−0.036	−0.198***
	(0.195)	(0.232)	(0.014)	(0.045)	(0.041)	(0.046)
Reference group: employ (employed)						
Unemp (unemployed)	0.0814	−0.200	−0.004	0.028	−0.028	0.005
	(0.279)	(0.344)	(0.015)	(0.047)	(0.051)	(0.0649
Notforce (not in the labor force)	−0.258	−0.206	−0.025	−0.047	−0.009	0.081**
	(0.215)	(0.263)	(0.012)	(0.056)	(0.041)	(0.040)
Reference group: Office and administrative support occupations						
Management, business, and financial operations occupations	−0.146	0.0802	−0.004	−0.036	0.018	0.023
	(0.263)	(0.296)	(0.015)	(0.067)	(0.043)	(0.051)

Table 5 (continued)

Variables	Model 1B—Coefficients		Model 1B—Marginal Effects			
	Musego	Handheld	Pr(mus=1,hand=1)	Pr(mus=1,hand=0)	Pr(mus=0,hand=1)	Pr(mus=0,hand=0)
Professional and related occupations	0.0151	−0.111	−0.005	0.009	−0.014	0.009
	(0.232)	(0.270)	(0.012)	(0.061)	(0.041)	(0.040)
Service occupations	−0.0862	−0.400	−0.025*	0.001	−0.041	0.065
	(0.250)	(0.297)	(0.014)	(0.063)	(0.044)	(0.060)
Sales and related occupations	0.0977	−0.122	−0.001	0.028	−0.020	−0.008
	(0.285)	(0.327)	(0.014)	(0.074)	(0.049)	(0.050)
Farming, fishing, and forestry occupations	−8.572***	−8.622***	−0.929***	−1.465***	−0.490*	2.884***
	(0.239)	(0.378)	(0.232)	(0.206)	(0.302)	(0.265)
Construction and extraction occupations	−0.342	0.0207	−0.019	−0.077	0.022	0.073
	(0.541)	(0.487)	(0.026)	(0.136)	(0.078)	(0.099)
Installation, maintenance, and repair occupations	−0.488	−0.420	−0.049*	−0.087	−0.020	0.156**
	(0.406)	(0.568)	(0.028)	(0.109)	(0.083)	(0.072)
Production occupations	−0.276	−0.865*	−0.059**	−0.018	−0.083	0.160
	(0.366)	(0.503)	(0.027)	(0.097)	(0.075)	(0.104)
Transportation and material moving occupations	−0.0415	−0.542	−0.030	0.018	−0.059	0.071

Table 5 (continued)

Variables	Model 1B—Coefficients		Model 1B—Marginal Effects			
	Musego	Handheld	Pr(mus=1,hand=1)	Pr(mus=1,hand=0)	Pr(mus=0,hand=1)	Pr(mus=0,hand=0)
	(0.418)	(0.479)	(0.031)	(0.098)	(0.064)	(0.113)
Reference group: hinc1 (less than 25.000 USD)						
Hinc2 (25,000 to 49,000 USD)	0.0227	−0.112	−0.004	0.011	−0.014	0.008
	(0.176)	(0.182)	(0.012)	(0.042)	(0.025)	(0.039)
Hinc3 (50,000 to 99,999 USD)	0.0907	−0.0875	0.001	0.024	−0.015	−0.010
	(0.179)	(0.202)	(0.013)	(0.042)	(0.026)	(0.043)
Hinc4 (more than 100,000 USD)	0.504**	−0.199	0.019	0.122***	−0.052*	−0.089**
	(0.204)	(0.228)	(0.012)	(0.046)	(0.028)	(0.47)
Reference group: married						
Widowed	−0.209	0.233	−0.0003	−0.058	0.039	0.020
	(0.299)	(0.307)	(0.017)	(0.074)	(0.046)	(0.059)
Single	0.410**	−0.241	0.012	0.103**	0.051	0.063***
	(0.183)	(0.201)	(0.011)	(0.043)	(0.028)	(0.042)
Divorced	−0.0174	−0.218	−0.012	0.007	−0.024	0.029
	(0.179)	(0.226)	(0.012)	(0.05)	(0.037)	(0.037)
Nchild	−0.284***		−0.016*	−0.063***	0.016**	0.063***
	(0.0952)		(0.011)	(0.020)	(0.008)	(0.020)
Disa	0.0870	−0.0832	0.001	0.023	−0.011	−0.010

Table 5 (continued)

Variables	Model 1B—Coefficients		Model 1B—Marginal Effects			
	Musego	Handheld	Pr(mus=1,hand=1)	Pr(mus=1,hand=0)	Pr(mus=0,hand=1)	Pr(mus=0,hand=0)
	(0.199)	(0.210)	(0.013)	(0.049)	(0.036)	(0.042)
Reference group: central						
Balance	−0.265*	0.153	−0.008	−0.066**	0.033	0.042
	(0.135)	(0.162)	(0.008)	(0.033)	(0.033)	(0.029)
Nometro	−0.380*	0.272	−0.008	−0.098*	0.053*	0.053
	(0.210)	(0.224)	(0.012)	(0.052)	(0.032)	(0.043)
Others	−0.194	0.0633	−0.008	−0.046	0.018	0.036
	(0.183)	(0.205)	(0.013)	(0.043)	(0.018)	(0.046)
Internet_use		−0.176**	−0.009***	0.001**	−0.020**	0.020*
		(0.0856)	(0.008)	(0.004)	(0.011)	(0.011)
ρ		−0.845***				
		(0.068)				
c^2		11889,78				
		(0.000)				
Log likelihood		−6615555,6				
AIC		13200000				
BIC		13200000				
Constant	−0.994***	−1.022**				
	(0.368)	(0.406)				
Observations	812	812	812	812	812	812

See Table 3

Table 6 Marginal effects for museum visits museum visits, handheld and internet

Variables	Model 2A—Coefficients		Model 2A—Marginal Effects			
	Musego	Internet	Pr(mus.=1,int=1)	Pr(mus.=1,int.=0)	Pr(mus=0,int.=1)	Pr(mus.=0,int.=0)
Internet	−0.478		−0.009	−0.126	0.009	0.127
	(1.334)		(0.019)	(0.362)	(0.019)	(0.362)
Musego						
Reference group: age1 (18−24)						
Age2 (25−34)	−0.188	0.119	0.005	−0.058	0.007	0.046
	(0.245)	(0.333)	(0.027)	(0.06)	(0.011)	(0.362)
Age3 (35−44)	−0.123	−0.615	−0.046	0.011	−0.015	0.050
	(0.248)	(0.391)	(0.040)	(0.065)	(0.016)	(0.070)
Age4 (45−54)	−0.0184	−0.0370	−0.003	−0.002	−0.001	0.006
	(0.264)	(0.412)	(0.031)	(0.065)	(0.011)	(0.075)
Age5 (55−64)	0.367	0.325	0.030	0.074	0.002	−0.107
	(0.258)	(0.400)	(0.0133)	(0.066)	(0.010)	(0.072)
Age6 (65+)	0.305	−0.349	0.019	0.106	−0.015	−0.071
	(0.320)	(0.407)	(0.036)	(0.076)	(0.019)	(0.084)
Reference group: male						
Female	0.301*	−0.277	−0.014	0.100***	−0.013	−0.072*
	(0.177)	(0.187)	(0.019)	(0.076)	(0.016)	(0.040)
Reference group: white						
Black	−0.579*	0.326	0.012***	−0.177***	0.020	0.144**
	(0.313)	(0.317)	(0.030)	(0.068)	(0.024)	(0.073)
Otherrace	−0.146	0.302	0.019	−0.060	0.011	0.030
	(0.225)	(0.300)	(0.26)	(0.052)	(0.015)	(0.059)

Table 6 (continued)

Variables	Model 2A—Coefficients		Model 2A—Marginal Effects			
	Musego	Internet	Pr(mus.=1,int=1)	Pr(mus.=1,int.=0)	Pr(mus=0,int.=1)	Pr(mus.=0,int.=0)
Edu (associate/university degree)	0.621***	0.947***	0.079**	0.097***	0.015	−0.191***
	(0.144)	(0.277)	(0.040)	(0.036)	(0.015)	(0.036)
Children_arts_school	0.751***	0.728***	0.066***	0.147***	0.006	−0.220***
	(0.189)	(0.253)	(0.020)	(0.046)	(0.015)	(0.052)
Reference group: employ (employed)						
Unemp (unemployed)	0.0707	0.301	0.023	−0.003	0.007	−0.027
	(0.280)	(0.596)	(0.050)	(0.095)	(0.012)	(0.075)
Notforce (not in the labor force)	−0.307	−0.648**	−0.052**	−0.035	−0.012	0.100*
	(0.228)	(0.295)	(0.026)	(0.054)	(0.020)	(0.059)
Reference group: Office and administrative support occupations						
Management, business, and financial operations occupations	−0.322	−1.167***	−0.089*	−0.002	−0.027	0.118
	(0.335)	(0.347)	(0.051)	(0.064)	(0.031)	(0.078)
Professional and related occupations	−0.0685	−0.781**	0.057	0.037	−0.021	0.040
	(0.288)	(0.337)	(0.046)	(0.057)	(0.020)	(0.070)
Service occupations	−0.203	−0.263	−0.022	−0.035	−0.004	0.061
	(0.243)	(0.301)	(0.024)	(0.059)	(0.009)	(0.067)

Table 6 (continued)

Variables	Model 2A—Coefficients		Model 2A—Marginal Effects			
	Musego	Internet	Pr(mus.=1,int=1)	Pr(mus.=1,int.=0)	Pr(mus=0,int.=1)	Pr(mus.=0,int.=0)
Sales and related occupations	0.0588	−1.151***	−0.081	0.097***	−0.033	0.017
	(0.354)	(0.386)	(0.059)	(0.071)	(0.035)	(0.082)
Farming, fishing, and forestry occupations	−6.009***	−6.267***	−0.556***	−1.149***	−0.064	1.769***
	(0.505)	(0.500)	(0.142)	(0.118)	(0.109)	(0.131)
Construction and extraction occupations	−0.419	−5.684***	−0.411***	−0.292	−0.152	0.271
	(0.623)	(0.412)	(0.192)	(0.195)	(0.159)	(0.178)
Installation, maintenance, and repair occupations	−0.493	−8.087***	−0.583**	−0.443**	0.218	0.358**
	(0.516)	(0.547)	(0.282)	(0.215)	(0.222)	(0.171)
Production occupations	−0.361	−0.362	−0.032	0.070	−0.003	0.105
	(0.346)	(0.466)	(0.039)	(0.091)	(0.012)	(0.196)
Transportation and material moving occupations	−0.377	−7.900***	−0.568**	0.461**	−0.214	0.221*
	(0.534)	(0.467)	(0.256)	(0.207)	(0.226)	(0.185)
Reference group: hinc1 (less than 25.000 USD)						

Table 6 (continued)

Variables	Model 2A—Coefficients		Model 2A—Marginal Effects			
	Musego	Internet	Pr(mus.=1,int=1)	Pr(mus.=1,int.=0)	Pr(mus=0,int.=1)	Pr(mus.=0,int.=0)
Hinc2 (25,000 to 49,000 USD)	0.122	0.816***	0.060*	−0.025	0.021	−0.056
	(0.231)	(0.272)	(0.032)	(0.046)	(0.026)	(0.056)
Hinc3 (50,000 to 99,999 USD)	0.233	0.478*	0.038	0.028	0.009	−0.075
	(0.188)	(0.290)	(0.024)	(0.043)	(0.015)	(0.051)
Hinc4 (more than 100,000 USD)	0.584**	1.018***	0.083**	0.083*	0.018	−0.13***
	(0.238)	(0.327)	(0.039)	(0.050)	(0.023)	(0.060)
Reference group: married						
Widowed	−0.160	0.0433	0.0001	−0.045	0.005	0.041
	(0.327)	(0.485)	(0.0236)	(0.082)	(0.015)	(0.091)
Single	0.494***	0.405*	0.038**	0.102**	0.002	−0.142***
	(0.186)	(0.227)	(0.017)	(0.045)	(0.009)	(0.050)
Divorced	0.0621	0.390	0.029	−0.011	0.0010	−0.027
	(0.181)	(0.273)	(0.028)	(0.044)	(0.010)	(0.049)
Nchild	−0.180*		−0.003	−0.048**	0.003	0.048**
	(0.0944)		(0.003)	(0.025)	(0.003)	(0.024)
Disa	0.156	0.921***	0.068***	−0.024	0.023	−0.067
	(0.325)	(0.316)	(0.028)	(0.072)	(0.034)	(0.069)
Reference group: central						
Balance	−0.259	0.237	0.012	−0.085**	0.011	0.062*
	(0.158)	(0.206)	(0.016)	(0.036)	(0.015)	(0.038)

Table 6 (continued)

Variables	Model 2A—Coefficients		Model 2A—Marginal Effects			
	Musego	Internet	Pr(mus.=1,int=1)	Pr(mus.=1,int.=0)	Pr(mus=0,int.=1)	Pr(mus.=0,int.=0)
Nometro	−0.405*	0.250	0.010	−0.125**	0.014	0.100*
	(0.230)	(0.287)	(0.025)	(0.052)	(0.016)	(0.061)
Others	−0.295*	−0.198	−0.020	−0.064	−0.00001	0.084*
	(0.178)	(0.234)	(0.018)	(0.046)	(0.007)	(0.049)
Internet_use		−0.221	−0.016*	0.016*	−0.006	0.006
		(0.183)	(0.009)	(0.016)	(0.010)	(0.010)
ρ		0.808***				
		(0.433)				
c^2		13407,86				
		(0.000)				
Log likelihood		−5378600,1				
AIC		10800000				
BIC		10800000				
Constant	−1.055***	−2.220***				
	(0.376)	(0.541)				
Observations	808	808	812	812	812	812
Variables	Model 2B—Coefficients		Model 2B—Marginal Effects			
	Musego	Internet	Pr(mus.=1,int.=1)	Pr(mus.=1,int.=0)	Pr(mus.=0,int.=1)	Pr(mus.=0,int.=0)
Internet						
Musego		2.416***	0.071***	−0.071***	0.200***	−0.200***
		(0.308)	(0.021)	(0.022)	(0.030)	(0.030)

Table 6 (continued)

Variables	Model 2B—Coefficients		Model 2B—Marginal Effects			
	Musego	Internet	Pr(mus.=1,int.=1)	Pr(mus.=1,int.=0)	Pr(mus.=0,int.=1)	Pr(mus.=0,int.=0)
Reference group: age1 (18–24)						
Age2 (25–34)	−0.254	0.236	−0.001	−0.070	0.027	0.043
	(0.215)	(0.298)	(0.001)	(0.056)	(0.027)	(0.053)
Age3 (35–44)	−0.132	0.018	−0.018	−0.018	−0.034	0.072
	(0.240)	(0.362)	(0.011)	(0.063)	(0.032)	(0.057)
Age4 (45–54)	−0.105	−0.136	−0.007	−0.022	−0.008	0.037
	(0.261)	(0.360)	(0.012)	(0.068)	(0.033)	(0.063)
Age5 (55–64)	0.280	−0.162	0.004	0.074	−0.022	−0.056
	(0.249)	(0.360)	(0.011)	(0.064)	(0.033)	(0.061)
Age6 (65+)	0.267	−0.750*	−0.014	0.088	−0.071	0.004
	(0.291)	(0.411)	(0.013)	(0.076)	(0.038)	(0.067)
Reference group: male						
Female	0.392***	−0.499***	−0.002	0.112***	−0.054	−0.055***
	(0.129)	(0.172)	(0.005)	(0.033)	(0.018)	(0.029)
Reference group: white						
Black	−0.672***	0.789***	0.003	−0.189***	0.087	0.100*
	(0.226)	(0.305)	(0.008)	(0.058)	(0.029)	(0.053)
Otherrace	−0.269	0.374	0.002	−0.077	0.039	0.035
	(0.220)	(0.316)	(0.008)	(0.059)	(0.032)	(0.047)
Edu (associate/university degree)	0.613***	0.415	0.031***	0.139***	0.015	−0.186***
	(0.134)	(0.256)	(0.008)	(0.034)	(0.024)	(0.034)

Table 6 (continued)

Variables	Model 2B—Coefficients		Model 2B—Marginal Effects			
	Musego	Internet	Pr(mus.=1,int.=1)	Pr(mus.=1,int.=0)	Pr(mus.=0,int.=1)	Pr(mus.=0,int.=0)
Children_arts_school	0.820***	0.280	0.034***	0.195***	−0.002	−0.226***
	(0.195)	(0.246)	(0.009)	(0.049)	(0.025)	(0.045)
Reference group: employ (employed)						
Unemp (unemployed)	0.120	0.126	0.007	0.025	0.006	−0.040
	(0.262)	(0.339)	(0.009)	(0.070)	(0.032)	(0.057)
Notforce (not in the labor force)	−0.264	−0.480	−0.022**	−0.051	−0.032	0.105**
	(0.221)	(0.344)	(0.001)	(0.060)	(0.032)	(0.048)
Reference group: Office and administrative support occupations						
Management, business, and financial operations occupations	−0.191	−0.948**	−0.034***	−0.019	−0.073**	0.125**
	(0.258)	(0.390)	(0.009)	(0.069)	(0.036)	(0.061)
Professional and related occupations	0.0362	−0.763**	−0.021***	0.031	−0.065**	0.054
	(0.238)	(0.337)	(0.008)	(0.064)	(0.032)	(0.052)
Service occupations	−0.176	−0.146	−0.010	−0.039	−0.006	0.056
	(0.248)	(0.324)	(0.009)	(0.066)	(0.031)	(0.063)
Sales and related occupations	0.189	−1.177***	−0.029***	0.081***	−0.104***	0.051
	(0.290)	(0.399)	(0.010)	(0.077)	(0.038)	(0.063)

Table 6 (continued)

Variables	Model 2B—Coefficients		Model 2B—Marginal Effects			
	Musego	Internet	Pr(mus.=1,int.=1)	Pr(mus.=1,int.=0)	Pr(mus.=0,int.=1)	Pr(mus.=0,int.=0)
Farming, fishing, and forestry occupations	−8.518***	−8.840***	−0.526***	−1.844***	−0.469***	2.839***
	(0.236)	(0.460)	(0.110)	(0.164)	(0.106)	(0.153)
Construction and extraction occupations	−0.279	−8.468***	−0.258***	0.180	−0.695***	0.773
	(0.593)	(0.533)	(0.054)	(0.157)	(0.098)	(0.166)
Installation, maintenance, and repair occupations	−0.355	−8.560***	−0.263***	0.164	−0.700***	0.799***
	(0.413)	(0.369)	(0.049)	(0.115)	(0.086)	(0.123)
Production occupations	−0.325	−0.0692	−0.012	−0.078	0.004	0.086
	(0.373)	(0.479)	(0.013)	(0.100)	(0.046)	(0.082)
Transportation and material moving occupations	−0.194	−8.057***	−0.243***	0.189	−0.663	0.717***
	(0.456)	(0.456)	(0.048)	(0.125)	(0.089)	(0.133)
Reference group: hinc1 (less than 25.000 USD)						
Hinc2 (25,000 to 49,000 USD)	0.0198	0.677**	0.021***	−0.015	0.056**	−0.061
	(0.181)	(0.270)	(0.008)	(0.047)	(0.025)	(0.046)

Table 6 (continued)

Variables	Model 2B—Coefficients		Model 2B—Marginal Effects			
	Musego	Internet	Pr(mus.=1,int.=1)	Pr(mus.=1,int.=0)	Pr(mus.=0,int.=1)	Pr(mus.=0,int.=0)
Hinc3 (50,000 to 99,999 USD)	0.168	0.232	0.012	0.034	0.014	−0.061
	(0.170)	(0.285)	(0.009)	(0.044)	(0.025)	(0.046)
Hinc4 (more than 100,000 USD)	0.491**	0.447	0.028***	0.108**	0.021	−0.158***
	(0.210)	(0.364)	(0.010)	(0.055)	(0.033)	(0.057)
Reference group: married						
Widowed	−0.165	0.262	0.002	−0.048	0.026	0.019
	(0.309)	(0.406)	(0.013)	(0.080)	(0.037)	(0.076)
Single	0.452**	−0.112	0.011	0.115***	−0.023	−0.12**
	(0.181)	(0.234)	(0.007)	(0.046)	(0.023)	(0.043)
Divorced	0.0251	0.222	0.007	−0.0003	0.017	−0.025
	(0.177)	(0.266)	(0.008)	(0.047)	(0.024)	(0.042)
Nchild	−0.244***		−0.008**	−0.060***	0.008***	0.060***
	(0.0904)		(0.003)	(0.022)	(0.003)	(0.022)
Disa	0.0872	0.898***	0.029***	−0.004	0.072***	−0.096**
	(0.205)	(0.280)	(0.009)	(0.054)	(0.025)	(0.047)
Reference group: central						
Balance	−0.232*	0.519***	0.008	−0.072**	0.050***	0.014*
	(0.141)	(0.192)	(0.006)	(0.036)	(0.018)	(0.034)
Nometro	−0.379*	0.662**	0.008	−0.113**	0.67***	0.039*
	(0.214)	(0.290)	(0.009)	(0.056)	(0.027)	(0.051)

Table 6 (continued)

Variables	Model 2B—Coefficients		Model 2B—Marginal Effects			
	Musego	Internet	Pr(mus.=1,int.=1)	Pr(mus.=1,int.=0)	Pr(mus.=0,int.=1)	Pr(mus.=0,int.=0)
Others	−0.265	0.0549	−0.007	−0.067	0.067***	0.061*
	(0.180)	(0.243)	(0.007)	(0.049)	(0.027)	(0.040)
Internet_use		−0.240*	−0.007*	0.007*	−0.020*	0.020*
		(0.139)	(0.003)	(0.004)	(0.011)	(0.011)
ρ		0.768***				
		(0.001)				
c^2		23150,95				
		(0.000)				
Log likelihood		−5335492,2				
AIC		10700000				
BIC		10700000				
Constant	−1.055***	−2.244***				
	(0.369)	(0.497)				
Observations	808	808	812	812	812	812

See Table 3

table) and the marginal effects (the following four columns): to take into account the marginal effects the probability has both onsite and online consumption equal to 1; on the probability of *musego* equal to 1 and the probability of *handheld* consumption equal to 0; on the probability of *musego* equal to 0 and *handheld* consumption equal to 1, and on the probability of both, *musego* and *handheld* equal to 0.

Results display that the *handheld* consumption does not have a strong impact on the probability to attend a museum physically. In fact, whilst the coefficient is not significant, a 0.043 marginal effect is found on the probability of having both *musego* = 1 and *handheld* = 1 (third column of Table 5), it shows a negative effect on the probability of having *musego* = 0 and *handheld* = 1 (fifth column). On the other side, the onsite attendance has a positive impact on the probability of online attendance, the marginal effect is equal to 0.114 of attending both types of events, whilst it is equal to 0.260 for having *musego* = 0 and *handheld* = 1 (Model 1B in the same table).

As far as concerns the other variables, for *age* category, as before, the effect is not very strong. In fact, this model does not show any statistical difference in favour of young people. On the other side, being female positively increases the probability to attend *musego.* In particular, a positive marginal effect of around 0.080 is found in the probability of having *musego* = 1 and *handheld* = 0, whilst a negative marginal effect of − 0.076 is found on the probability of having both events equal to 0 in the Model 1 and equals –0.051 in the case of *musego* = 0 and *handheld* = 1. Being black decreases the probability of attending a museum and increases the probability of having both events equal to zero.

As expected, a strong effect is found for the education variable together with the *children_arts_school* variable (school aged children being taught art or going to a music/art museum or gallery or attending a live music, theatre or dance performance in school/outside school), which shows a positive probability in attending onsite, whilst a negative impact on the probability that both events are equal to zero. As for the variables related to occupation, a strong negative impact is found for *production occupations*, compared with people occupied in the *office and administrative support occupations*. This is not a surprising effect since working in this category usually implies that individuals are better educated and are working with new technologies. However, as before, the lowest, although highly significant, probability to participate is found in the case of *farming, fishing, and forestry occupations*.

The impact of income becomes bigger when we move to the highest level. In fact, the variable *hinc4* shows a positive and significant effect on the probability of physically attending a museum, and is negative on the probability of having both events equal to zero. For what concerns the variables linked to time availability, being single shows a positive impact whilst the number of children decreases it. Finally, living in a *balance* or in a metropolitan area turns out to have a lower marginal effect compared with people living in a central area.

Finally, Table 6 shows that there is no impact of *internet* consumption of visual arts on *musego*, whilst a strong significant effect of onsite consumption on the *internet* is found. In the latter case, we find a marginal effect of 0.071 for the impact that *musego* has on the probability of having both events equal to 1 and a marginal effect of 0.200 on the probability of having only *internet* = 1. As for the other variables, the sign and the magnitude are similar to those displayed in the previous paragraph.

Summing up, this paper shows evidence that the internet consumption of visual arts has no relationship over the probability of museum visits, whilst a positive and statistically significant relationship of visiting over the probability of access via the internet is found.

The positive impact of *musego* over both *handheld* and *internet* means the reinforcement of online visits for different types of digital access. This means that after a physical visit to a museum, an individual can continue his/her enjoyment, even though he/she is located in another place compared to the museum. On the other hand, we do not find the same reinforcement after the digital access through both *handheld* or *internet*. In fact, both variables are not statistical significant. Hence, our results suggest that a complementarity exists between onsite and online consumption of visual arts. This complementarity highlights that ICTs can expand the audience of cultural participation.

However, a word of caution should be spent on these results, since they are obtained using a cross-sectional dataset. Even though the recursive bivariate probit model is applied where a variable z that explains Y2, but not Y is added, to better capture the complementarity or substitutability between onsite and online consumption a panel data approach would be preferred.

5 Conclusions

Information and communication technologies as general purpose technologies have reached different aspects of production, consumption, and daily life (Castiglione & Infante, 2014). ICT has provided many opportunities to sustain and implement public and private activity (Kourtit et al., 2017). In fact, traditional participation in the arts, in the form of attending performances and visiting cultural institutions, is no longer the sole or even the main way of enjoying pleasurable and enriching cultural experiences. Technological changes have dramatically altered the way in which art and entertainment are produced and consumed. In the era of ICTs, when many individuals are digitally engaged, technological progress has also influenced cultural consumption, bringing new opportunities through the use of mobile devices and the internet. For many cultural manifestations, the development of ICTs has introduced new ways of transmitting or mediating those information cultural goods, and this should be taken into account by the managers of cultural institutions. Despite the importance and potentiality of digital devices in participation in the visual arts, very few studies have been conducted in this field, with most studies focusing on the traditional onsite attendance of a museum. To contribute to the changes that digital technologies have determined on cultural participation, this paper jointly explores the choice of attendance at museums and art galleries and/or media and digital engagement with visual arts for digital users.

By using data from the US 2012 *Survey of Public Participation in the Arts*, we explain those choices in terms of variables that account for differences in cultural preferences and resources, and for differences in other contextual factors. Results show evidence of similar effects on both types of cultural consumption (*musego* and *handheld/internet*) of those variables that determine cultural capital, early socialisation and some kind of taste for the visual arts. However, when analysing the results for variables that incorporate the effect on the participation decision of the availability of other household characteristics, some differences are found. The most remarkable ones refer to the impact of race, gender, families with children attending arts school, income and type of occupation.

By estimating both multinomial logit and recursive simultaneous bivariate models, we have distinct direct and indirect effects for the two alternative forms of digital engagement. We have found that there is a trade-off between internet consumption and onsite visits. Visiting museums and art galleries has a positive impact on the digital access to visual arts, both through handheld and mobile devices and via the internet, whilst the same impact is not found for internet access on museum attendance. There are a number of circumstances that help to explain these results. Mobile access is an activity that can be done onsite whilst visiting museum and art galleries, whilst through desktop internet access this is not possible. For all three alternative pathways of access considered in this research (visits, access through mobile devices, and via the internet), some new results on participation in the arts are also recorded. Particularly, for the live dimension, there is a feminisation of participation, positive effects of income and urban habitat, as well as a positive effect for working in an occupation that could determine whether an individual belongs to the most educated class. In fact, for all types of access, education present the strongest effects.

Concerning the cultural policies, the managers of cultural institutions, in the design of new products, should take into account the changes in cultural engagement for each type of participation. For museums, the exhibitions they hold are not the only way of displaying their cultural assets, so digital content and services should be oriented to alternative forms of digital media accounting for their potential complementary or substitution effects. In fact, since visits positively affect the use of handheld/internet devices (complementarity effect) in visual arts consumption, whilst internet consumption does not affect onsite visits (substitution effect) managers should focus on ameliorating the physical exposition and on introducing some forms of online fees for their online collection, to increase cultural institutions revenues.

In conclusion, since ICT devices are permeating the everyday lives of individuals, and given that consumers use their electronic devices to be informed and decide about how to allocate their resources for creating pleasant cultural experiences, more research on the joint influences of alternative ways of accessing cultural institutions should be conducted. For example, in the case of social networks, consumers use that technology to record, disseminate, and transform traditional tangible cultural goods into new digital cultural goods that can be consumed by other members of the same community, extend and enrich the cultural experience; this could all be investigated.

Acknowledgements We would like to thank the Editor, the anonymous referees and Davide Infante for their insightful comments and suggestions, which helped to improve the quality of the paper substantially.

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