TRAINING MODEL AND INTERVIEWER PERFORMANCE IN THE PERMANENT POPULATION CENSUS[1]

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Abstract. Training interviewers is crucial in survey design to minimize interviewer effects, which impact non-sampling errors (partial non-response, refusals, and measurement errors) and data quality. Istat has developed expertise in training interviewer networks and continuously works on strategies to improve and harmonize its training model, adapting to societal changes and respondents' lifestyles.

This study examines the effect of interviewer training on survey performance to improve the training program. The data analyzed relate to the performance of 5,894 interviewers trained for the 2023 Italian Population Census "List" survey.

To explore the relationship between training and fieldwork performance and identify interviewer profiles, we used a statistical classification method (decision tree), considering socio-demographic and geographical factors as potential covariates.

The results represent a crucial step toward the ongoing use of statistical methods to enhance the data collection process.

1. Introduction

The quality of produced data depends significantly on the quality of the data production process. In recent decades, awareness of this connection has solidified, leading to greater attention on both upstream (design) and downstream (processing and analysis) data quality.

In the realm of Official Statistics, Eurostat has outlined quality principles for both the statistical process and the statistical product (Eurostat, 2017). These principles have been adopted by Italy through the Codice Italiano per la qualità delle Statistiche Ufficiali (Istat, 2022), recognized as a best practice for the production of Official Statistics internationally. This is complemented by the ESS Quality Assurance Framework, or ESS QAF (Eurostat, 2019), which identifies methods and tools at the institutional or process level to ensure compliance with the Code's principles, thereby promoting good practices. While the Code's principles tell us *what to do*,

[1] The authors share contents and views expressed in this paper. However N. Mirante drew up the sections 1 and 2; A. Bernardini the section 3 and N. Balì the section 4.

the GSBPM (Generic Statistical Business Process Model) guides us on *how to do it*. Developed by UNECE (2019), the GSBPM describes and defines the set of processes necessary for the production of official statistics, providing a standard framework and harmonized terminology to assist statistical agencies in modernizing their statistical production processes and sharing the methods used. Additionally, it serves as a model for evaluating and improving the quality of these processes.

Since the 1990s, Istat has systematically worked to ensure the quality of statistical information and the service provided to the community. This has involved adopting the aforementioned principles and models and drafting various quality guidelines (Istat, 2012; Istat, 2018) to illustrate the principles to be followed in the design, execution, and control of a statistical survey, as well as to describe the quality requirements that statistics must meet.

These guidelines also include principles concerning interviewers and their training, specifically:

- The principle "D.2.4. Interviewers" from the Istat guidelines for the quality of statistical processes states: "*Interviewers must be selected, trained, and monitored in such a way as to ensure that the data collected are as accurate* as *possible"* (Istat, 2012);
- The principle "C.2." from the SISTAN quality guidelines for statistics states: "*To ensure the quality and completeness of the information collected, careful attention should be paid to the selection and training of interviewers. Additionally, the data collection phase should be monitored during the process and evaluated afterward using appropriate tools and objective indicators"* (Istat, 2018). This principle identifies two monitoring indicators for interviewers:
    - Average daily number of interviews per interviewer (workload);
    - Total response rate per interviewer (number of completed interviews out of those planned).

Among the various aspects to consider in the design and execution of a direct statistical survey, one of the most important is the training of interviewers. Proper training is crucial to minimize the interviewer effect, which significantly impacts non-sampling error (e.g., partial non-response, refusals, and measurement error), and thus the quality of collected data. However, interviewer training is often an overlooked aspect in reducing interviewer effects in interviewer-administered surveys (Daikeler and Bosnjak, 2020).

Istat has extensive experience in training survey networks, which has undergone various modifications over the years in a continuous search for new training strategies to improve and harmonize the proposed training model, keeping pace with societal changes and respondents' lifestyles, thereby generating economies of scale.

Istat has consistently placed great emphasis on education, implementing new strategies to ensure a continuous and efficient training model, especially during the transition to the new census framework. This approach takes into account economic constraints and available resources. Significant innovations have been introduced in the training strategy, resulting from a thorough examination and analysis of various training processes used within the Institute. The goal is to design a permanent training model with a circular perspective.

Initially, training followed a waterfall model (e.g., central Istat, territorial Istat, municipalities). With Istat's modernization, training became direct and centralized, allowing interviewers to be trained directly by Istat. This resulted in the standardization of the training process and control over its effectiveness and efficiency. Another significant change introduced in the training of survey networks was the shift from on-site training to remote or blended training, including self-learning modules (FAD) [Istat, 2019]. Finally, during the COVID-19 pandemic, it was necessary to rely entirely on remote training.

Over the decades, Istat has developed substantial expertise in training survey networks. This knowledge is supported by various studies conducted by the Institute over the years to evaluate the effectiveness and efficiency of the different training models implemented (Istat, 2005; Istat, 2006; Istat, 2010; Balì and Federici, 2014; Balì, 2015; Balì *et al.*, 2023).

The importance of information produced by official statistics has led to constant attention to data quality in all survey processes, particularly in the Census. The Census process is characterized by complexity and multidisciplinarity, requiring diverse competencies. A significant contribution to the quality of collected data comes from individuals involved in survey networks, emphasizing the central role of network training.

To address this, the Institute has heavily invested in training survey networks, creating well-structured training programs. Notably, the redesign of network training was part of the innovative approach to the new Census strategy, incorporating interdisciplinary methods. The adoption of blended learning - an ongoing learning approach involving cross-cutting skills - was chosen.

Furthermore, the Covid-19 pandemic accelerated the introduction of innovative elements in training delivery. Traditional in-person training sessions shifted to virtual classrooms, utilizing communication and collaboration platforms. This adaptation highlighted the need for flexibility and adaptability in the training approach.

The aim of our study is to explore how the training program can influence interviewers' performance in the field and to try to profile the surveyors.

2. Methods

For this study, we utilized interviewer performance data from the survey network for the 2023 edition of the "permanent population and housing census – Lista".

Before the fieldwork, interviewers were required to complete an online self-learning course (Formazione a Distanza, FaD) on Moodle2. The FaD comprised 14 consecutive video lessons. Upon viewing each video lesson, the student had to pass a corresponding intermediate test. Only after successfully passing this test was the interviewer allowed access to the subsequent video lesson and its associated intermediate test. This process continued sequentially until all modules were completed. At the end of this educational path, the student was granted access to the final test, which required a minimum score of 90% for successful completion.

On the Moodle platform, interviewers also had access to additional materials such as manuals and guides. These resources were available throughout the survey period to support the interviewers when necessary.

We analyzed the data of 5,894 interviewers who met the following inclusion criteria: 1) at least one family assigned; 2) at least one interview conducted.

To investigate interviewer performance, we focused on two specific phases: 1) performance during training; 2) performance during fieldwork. The chosen parameters were "Score in the post-training learning test" and "Number of attempts to pass the test" for the training phase, and "Number of face-to-face interviews out of the total number of interviews conducted" for the fieldwork phase.

Other factors considered were: age class (18-29 years, 30-44 years, 45-59 years, and over 59 years), gender, educational level (middle school, high school, degree), geographical data (North, Centre, South), new/expert interviewer status, and whether the FaD was completed before or after the fieldwork.

To classify this population, we used the CHAID (Chi-squared Automatic Interaction Detection) tree classifier, which employs the chi-square association statistic to define, at each level, how to subdivide cases into subgroups, starting from the entire study dataset (Ritschard, 2013). This non-parametric method selects the independent variable (predictor) with the strongest interaction with the dependent variable at each step. Categories of each variable are merged if they do not differ significantly from the dependent variable. At each node, the algorithm splits the cases based on rules for different categories of independent variables, so the resulting subsets are most associated with the performance variable.

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[2] Modular Object-Oriented Dynamic Learning Environment (Moodle) is a computer system for creating and sharing educational materials online

3. Results

The classification tree is an extremely useful tool for presenting the results of a recognition model for specific profiles, as it translates these results into easily understandable rules, unlike the often complex parameters of other predictive models. The dependent variable we chose is “the number of face-to-face interviews out of the total number of interviews conducted”, which we consider a measure of the interviewer's performance.

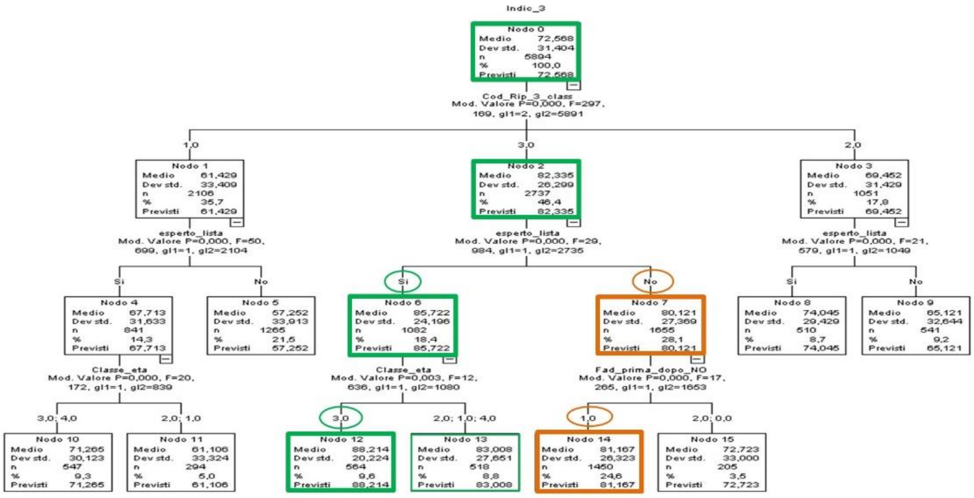
We hypothesized that certain contextual factors - geographical and spatial in nature, demo-social characteristics such as age and educational qualification, and the training behavior of the survey network members - might influence the interviewer's performance in the field. Our goal was to identify interviewer ‘profiles’ that could contribute to more efficient survey networks. The independent variables we considered included the interviewer's socio-demographic variables (age, gender, and educational qualification), census survey experience, and training-related variables (completion of the training course within the required timeframe, overall grade in the final test of the training course, and the number of attempts to pass the final test).

Although this first application does not provide a perfect classification of the interviewers, nor does it describe a precise profile or fully explain the relationship between training and performance, the tree is still very useful for describing individual and territorial profiles associated with different training characteristics and interviewer behaviors during fieldwork.

The results of the tree show that the first subdivision rule corresponds to territory. In the application, three levels of the territorial type variable (geographical breakdown, region, and province) were considered as independent variables. For easier interpretation, Figure 1 shows the analysis conducted with the most aggregated variable (geographical breakdown).

This results in a total of 16 nodes, with 9 terminal nodes representing the best classifications for the chosen model. At the first level, geographical breakdown constitutes the best classification step. Moving to the next level, for all breakdowns, the discriminating factor is the variable ‘experience’. If the interviewer is experienced and falls within the middle age range, their field performance is the best (Node 12). Together with the younger and older age groups (Node 13), they account for 18% of the interviewers. This is crucial because a survey network with extensive Istat survey experience certainly ensures better data quality. Conversely, if there is no survey network with experience, the model shows that training is fundamental to the interviewer's work. Node 14, which includes about 25% of the observed population, represents the cluster of units that, despite having no work experience, completed the training before conducting interviews in the field.

Figure 1 - *Performance during the fieldwork: classification tree result*



The work will continue to identify the best reclassification strategy for the variables, focusing on the two phases under consideration: performance during training and performance during fieldwork.

4. Conclusions

In interviewer-administered surveys, the interviewer's role is pivotal in ensuring the collection of high-quality data. While appropriate training is a fundamental factor in enhancing field performance, our study reveals that additional elements - such as socio-demographic characteristics of interviewers, prior census survey experience, and geographical context - play a significant role in shaping outcomes.

The decision tree analysis underscored the importance of territorial differences: interviewers operating in Southern Italy outperformed their counterparts in the North and Centre. This finding could reflect regional disparities in engagement strategies, cultural attitudes toward surveys, or broader socio-economic characteristics of the interviewers. Moreover, prior experience as a census interviewer emerged as a critical determinant of achieving high rates of face-to-face interviews, highlighting the value of maintaining an experienced network of interviewers.

For new interviewers, the results indicated that completing training prior to the commencement of fieldwork was strongly associated with improved performance.

This underscores the importance of well-structured and mandatory training programs. Consequently, the evidence suggests that training should be tailored to the needs of different interviewer profiles, with comprehensive programs for new recruits and refresher courses for seasoned professionals.

Nonetheless, the findings also point to the necessity of more granular analyses to better comprehend and address performance disparities. As previous research (e.g., Bernardini et al., 2014) has noted, challenges in reaching households vary significantly even within broadly aggregated territorial classifications. Municipal-level complexities - including geographical size, population density, and socio-economic conditions - substantially influence the data collection process. In this context, the introduction of a composite index, as proposed by Bontempi et al. (2024), represents a promising advancement. Such an index could synthesize interviewer socio-demographic attributes, territorial characteristics, and training behaviors, enabling more precise profiling and targeted interventions.

This study represents a critical step toward optimizing interviewer training and resource allocation. Developing differentiated training modules based on interviewer profiles, alongside strategies tailored to specific territorial contexts, offers a promising pathway for enhancing the efficiency of survey networks and, ultimately, the overall quality of collected data.

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