On the Efficient Supply of Cultural Goods

The case of Dutch Museums

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Abstract

Facing funding uncertainties and reduced subsidies, the cultural sector is forced to use its limited resources as efficiently as possible. The question of how to measure the efficiency of a cultural organisation has been address in the literature over the past three decades. While cultural goods and services cannot be appropriately valuated using conventional market-oriented measures alone, the efficiency of cultural organisations can be measured using a variety of methods. The most common and versatile method is the Data Envelopment Analysis (DEA) approach, a method that has been used to assess theatres, cinemas, libraries, and museums. Previous studies have assessed the efficiency of museums in Italy, Spain, Czech Republic and Belgium, among other countries. Dutch museums, surprisingly, have not been researched thus far. To address this gap in the literature, this master thesis uses two DEA models to assess the efficiency of 17 Dutch museums over three years. Furthermore, it deviates from previous DEA models by including variables related to museums' digital goods and services. The analysis finds that most museums are operating efficiently in each of the evaluated years. It also finds that the remaining museums are severely inefficient. These findings are markedly higher than those of previous studies and suggest further investigations to better ascertain the reasons for such differences.

Keywords: museums, efficiency, data envelopment analysis, performance assessment

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1. Introduction

Museums, as a core cultural industry, play a vital role in many nations' cultural industries and cultural policy (Throsby, 2008). Not only can museums provide social and economic benefits to a community and nation, but they can also play an integral role in the formation and maintenance of local, regional, national, and cultural identities (Frey and Meier, 2003; McLean, 2005; Sandell, 2007). In the public policy realm, these benefits are utilised to justify the public support and funding of these and other cultural and creative institutions (Towse, 1994). In the Netherlands, as of 2021, the public funding scheme has shifted to a more streamlined and financially stable approach guaranteeing funding in four-year cycles. In the case of many museum sectors around the world, increases in efficiency can positively impact the likelihood of receiving public funding which is critical to institutional survival (Basso and Funari, 2004). However, the uncertainty of how well Dutch museums are performing may impact how effectively subsidies are distributed and how well institutions perceive themselves to be performing.

Current public funding for the cultural and creative industries earmarked by the Dutch government has shrunk by 10% since 2009 (Schrijen et al., 2019; Tweede Kamer, 2020), thus forcing cultural institutions to compete over a shrinking and uncertain pool of resources available to them. According to ICOM's definition of museums, their primary tasks include research, collecting and conserving, and interpreting and exhibiting (ICOM, 2022). Museums are, therefore, complex multioutput firms, posing difficulties for the measurement of their efficiency and for determining a sample's efficient frontier due to the absence of a single output that all museums prioritise equally. The efficient frontier of a sample highlights the cases of best practice in terms of the efficient use of a set of inputs to produce a set of outputs and is produced by data envelopment analyses (DEA). This thesis will use the DEA method to answer the following research question:

How technically efficient are Dutch museums?

The goal of this research is to contribute to the growing field of efficiency measurement in the cultural industries, by investigating public museums in the Netherlands, a country in which this type of research has not been conducted in the past.

The measurement of a museum's efficiency can have direct public policy implications, for example in determining appropriate funding allocation. Allocating resources without appropriately measuring museum efficiency and the resources an institution requires to produce desired outputs may lead funding bodies to resort to alternative criteria. These criteria could be based on an institution's perceived cultural or artistic values, which are not indicators of an organisation's input-output processes and efficiency. This is problematic for the accountability of public expenditure since the allocation of subsidies could be based on subjective evaluations rather than on transparent and objective methods. Distributing subsidies based on ambiguous interpretations without a standardised approach is bound to lead to inappropriate funding of the museum field.

The motivation for this research is linked to its social relevance. It is socially relevant to quantify Dutch museum efficiency because it provides museum funding policy-makers with a useful metric to include in their decision-making processes. Identifying inefficient museums can inform policies to incentivise museums to strive for (increased) efficiency and to divert scarce surplus subsidies to more efficient organisations. From the museum side, efficiency analyses can provide management with relevant quantitative data on whether they are operating efficiently and at an appropriate scale of operations. Additionally, in the case of inefficiencies, managers would be able to reallocate resources according to their organisation's priorities and mission.

This research will be quantitative in nature and apply DEA methods to measure the efficiency of Dutch museums. This analysis method has been used by numerous past studies and by a significant number of other efficiency analyses focusing on museums. Therefore, by focusing on Dutch museums using methods applied in other studies, this research is scientifically relevant as it contributes to addressing the gap in research on museum efficiency.

The following chapter will lay out the theoretical framework that informs this research, as well as a review of the literature on museum efficiency and DEA. The subsequent chapter discusses the methodology, such as the research design, method and models, and data collection process. The ensuing two chapters will present the results of the methodology and provide an extensive discussion of the results, their implications and limitations. Finally, the thesis will conclude with a chapter summarising the main points and answering the research question.

2. Theoretical Framework

This chapter presents the theoretical foundation of this research. It establishes the origins and motivations for the measurement of performance and efficiency in the cultural sector, as well as the challenges posed by the ambiguous values of culture. In addition, it provides information specific to the Dutch museum field which contextualises the uses of efficiency measurement for museums and funding bodies. Following this is a review of various efficiency measurement methods that have been used to assess the cultural and museum sectors in the past. The chapter ends with a review of the existing literature on museum efficiency using DEA, to highlight their similarities, differences, and challenges.

2.1 Performance measurement in the Cultural Sector

For-profit firms traditionally strive to maximise their produced output relative to their available inputs. This relationship between inputs and outputs is the technical efficiency of a firm, a relationship which differs from allocative efficiency, which refers to a firm's efficiency in matching output with market demand (Farrell, 1957). Considering these differences, this paper researches the technical efficiency of museums, rather than their allocative efficiency as museums take educational, cultural, and social values and desired outcomes into account when allocating resources across their multiple outputs. Allocative efficiency may lead to overlooking museum activities that are essential to its organisation and function, and yet are not sufficiently demanded by the market and consumers. It is important to highlight the distinction between efficiency in transforming inputs into outputs and the effectiveness of the produced output concerning an organisation's goals. Non-profit organisations that dominate the public and cultural sectors, such as museums and theatres, have striven to achieve various social, educational, and artistic outcomes using their outputs, a qualitative dimension that evades standardised quantification and measurement (Pignataro, 2002). These outcomes necessitate a certain degree of effectiveness by organisations when producing goods and services. In this sense, effectiveness differs from efficiency because it relates to social, cultural, or other, values and results of a produced output, rather than the efficiency of its production process. These two characteristics of cultural production are not mutually exclusive; however, they can also occur independently of each other. For example, a museum could effectively educate and be inclusive of marginalised groups through their produced activities, but they may not necessarily be efficient in organising them. Rather than prioritising a pure maximisation of outputs, i.e., technical efficiency, cultural organisations must strike a delicate balance between the two characteristics of output depending on their mission. The public good attributes and non-market values of cultural goods and services (Throsby, 2003) complicate the assessment of an institution's necessary resources to produce a desired output. By extension, these difficulties can affect public policy and firm-side allocation of resources as well (Hadida, 2015).

The improvement of technical efficiency and accountability in the cultural industries has been pushed by governments around the world since the late 20th century (Ahn et al., 2017). The Netherlands stands out in mainland Europe because of its long-lasting custom of tracking public sector performance beginning in the 1970s with the implementation of measurement-based policies (van Dooren et al., 2015). While Dutch museums operate at arm's length from political influences, they remain accountable to their external funding sources, which are commonly local municipalities (Overman, 2021). However, despite frequently employing performance indicators to assess cultural organisations, a governmental audit of the Dutch Ministry of Education, Culture and Science's ("OCW") 2005-2008 cultural policy states that "not all goals [of the cultural sector] can be expressed in quantitative target values" (*BRIEF VAN DE STAATSSECRETARIS VAN ONDERWIJS, CULTUUR EN WETENSCHAP*, 2011, p.1). This highlights a significant disadvantage of a measurement-based policy that is not sufficiently developed for the cultural sector. Indeed, interviewed Dutch museum directors state that the primary use of admittedly ineffective performance indicators was to protect municipalities from problems stemming from higher governmental entities, rather than to improve the cultural sector's performance (Overman, 2021). Further, while the OCW established objectives for the cultural sector, such as public reach, increasing social and financial support, and the diversity of cultural goods, not all goals were operationalised. As a result, metrics that were more suited for quantitative assessment, such as an organisation's self-generated funds and its number of visitors, took on a more significant role in performance assessment. In a survey of 46 municipalities, Overman et al. (2018) found that most municipalities utilise the number of museum visitors and inter-organisational collaborations as primary accountability metrics for the museums they fund. Relatively little attention is paid to cultural diversity, organisational management and self-generated funds. Strikingly, only one of the 14 identified performance indicators referred to a core museum activity: cultural education. Other core tasks, such as researching, collecting, and conserving, are not addressed by the sampled municipalities. The exclusion of these tasks is potentially due to the mistaken belief that easily captured metrics always align with what is thought to be measured, i.e., visitor numbers and performance. Clearly, by only partially addressing a museum's multiple outputs, this system of museum performance evaluation is insufficient. Therefore, the development of an appropriate accountability system necessitates input from both the principal and agent to align expectations and goals (Overman, 2021).

The concentration on performance measurement at the end of the 20th century was also very pronounced in the United Kingdom, which led to studies measuring the British cultural sectors' performance, in some cases focusing on museums (Ames, 1994; Evans, 2000; Selwood, 1999). These developments were ushered in by austerity measures and cutbacks in public funding for the cultural sector due to financial hardships and recovery following the 1980s recession. They were introduced under the belief that further control over and accountability from the cultural sector were necessary to improve performance and resource management. In the last decade, the Netherlands have introduced quantitative performance measurements and requirements for funding and significantly reduced public spending on the cultural sector starting (Boekmanstichting, 2015). These effects on the cultural sector were further exacerbated by the recent COVID-19 pandemic.

It may be expected that, occasionally, performance assessments will be met with resistance as this accountability process is inextricably linked to funding. This is the case of New Zealand, for example, where Hooper et al. (2005, p.426) found that the arrival of efficiency measurement was opposed by museum professionals whose, "professional identity is more strongly tied to notions of intrinsic, aesthetic, social and cultural value rather than economic value or government dictate". Similarly, in the case of English museums, assessment procedures were resisted due to the perception that funding bodies would control museum outputs to meet market demand above all else. Criticisms of performance indicators, and the wider trend of performance measurement, were based on uncertainties regarding how data would be presented, interpreted and acted upon by funding bodies (Selwood, 1999). Consequently, the attempts to quantify the provision of cultural goods and services, especially in terms of economic value and efficiency, were seen as putting culturally, historically, or artistically valuable goods and services at risk due to their potentially insufficient demand yet relatively high input costs.

These types of resistances from within the sector, however, have not prevented the rise of performance measurement of cultural organisations in the Netherlands, the United Kingdom and elsewhere. This has led to a fraught relationship between museums and funding bodies that can be characterised by an asymmetric information situation. In this relation, the agent (museum) is not transparent regarding its efficiency and performance, while the principal (funding body) does not divulge what funding is available for future initiatives, goals, and the sector (Zorloni, 2010).

Although the increase in the performance measurement of the cultural sector finds its origin in governmental bodies (Chiaravalloti, 2014), these measurements can form the cornerstone of an institution’s internal evaluation processes. The resulting analysis can provide beneficial insights about the use and distribution of scarce resources, and the causes of inefficiencies; it allows benchmarks that can help institutions to operate more efficiently, and more effectively. Cultural institutions, particularly non-profit firms which do not answer to shareholder-owners, can benefit from performance evaluations, as these would provide managers with quantitative information, and increase internal and external accountability, i.e., within the firm and to outside sources of funding (Soren, 2000). Museums, along with other cultural institutions, frequently make use of a combination of public and private funding, such as from private and corporate donors and grants. In a field with limited resources and many firms, it is essential for a museum to be transparent by laying forward the (efficient) use of resources to secure funding (Basso and Funari, 2020), a requirement often set forth by governmental funding bodies, grants, and donors (Basso et al., 2018). However, despite the top-down push for the quantifying of cultural industrial performance, many approaches did not sufficiently, if at all, account for the qualitative and subjective dimension of the cultural industries, particularly effectiveness and outcomes (Taheri and Ansari, 2013). Symbolic and experiential values of culture are insufficiently addressed by instrumental public policy which adopts limiting quantitative measures that focus on the purely economic impact of culture (Belfiore, 2007).

Exclusive reliance on quantitative approaches, without supplementing them with methods to assess cultural, social, and artistic outcomes and values, may lead to their under-provision and therefore, social cost. Therefore, for performance measurement, it is key to develop and utilise effective measurement strategies that account for all dimensions central to the firm's activities and organisation. Along this line, it is crucial to prevent the conflation of four related, and at times, overlapping concepts: effectiveness, i.e., the realisation of goals and outcomes (Gilhespy, 1999); social efficiency, i.e., the allocation of resources to the wider benefit of society while considering production and distribution (Johnson and Thomas, 1998); allocative and technical efficiency defined previously. Allocative and social efficiency go together, while also requiring separate measures. The former refers to the efficient distribution of resources to cultural goods that are most valued by society, while the latter additionally accounts for the production and distribution of produced outputs, addressing equity and accessibility. It is important to differentiate them to ensure that one measures the intended concept. Each of these aspects refers to different dimensions of an organisation's activities and all fall under the umbrella of performance measurement. Consequently, researching an organisation's performance according to each concept necessitates differing methods and considerable analysis. Therefore, to limit the scope of this research, only the technical efficiency of museums was assessed.

To improve the efficiency of input-to-output processes, a cultural organisation must first record and measure its activities. This enables it to evaluate and improve them (Kaplan, 2009). Nevertheless, the measurement stage of this undertaking is complicated by the nature of cultural organisations. Traditional efficiency measurement approaches tend to use profit margins or returns on investment as primary indicators of a firm's performance and efficiency (Abujarad et al., 2010). These metrics may only be appropriate for some of the cultural industries where efficiency and profit maximisation are of importance, and that produce and market cultural goods and services as commodities, such as in the for-profit publishing, media and video game industries. Hence, they have motivations akin to those of private corporations in other industries in the sense that they employ specific strategies to maximise profit (Garnham, 2006). The museum sector, however, stands in stark contrast to this segment of the cultural sector as they are primarily non-profit institutions (CBS, 2021; ICOM, 2022), thus calling for a different measurement approach (Taheri and Ansari, 2013). Critically, museums have multiple outputs, such as exhibitions, educational programmes, research projects, and cultural events which are not focused on uniformly by institutions. Institutional output priorities vary across the sector: for example, a museum may focus on its educational outputs, while another prioritises its research outputs (Basso and Funari, 2004). This leads to the necessity of a flexible measurement approach that accounts for these differences when assessing.

2.2 Efficiency Measurement in the Cultural Industries

This section will provide a review of how the efficiency of the cultural sector, and museums in particular, have been measured and researched in the past. Pignataro (2002) and Navarrete (2020) note that the wider performance of firms and museums can be measured using methods such as the Balanced Scorecard (BSC) and Performance Indicators (PI). Despite this, (technical) efficiency is very frequently measured using data envelopment analysis (DEA) approaches.

2.2.1 Data Envelopment Analysis

The non-parametric DEA method is widely used to measure firm efficiency across industries, but in scholarly work focusing on cultural industries, this method has seen widespread application. This paper’s purpose is not to provide a comprehensive overview of the body of work employing this method. To present its wide-ranging use in the cultural and creative industries, in the last five years, DEA was employed to assess the efficiency of:

- libraries (Bernardo et al., 2020; Del Barrio-Tellado et al., 2021; Del Barrio-Tellado et al., 2023; Guajardo, 2018; Guajardo, 2020; Guccio et al., 2018; Holý, 2022; Jetmar, 2023; Kim et al., 2020; Neto and Hall, 2018; Saliman et al., 2022; Šebová et al., 2019; Tavares, et al., 2018; Vrabková, 2019; Wang and Chen, 2020)
- performing arts (Baldin and Funari, 2022; Bruno et al., 2023; Castiglione et al., 2018a; Castiglione et al., 2018b; Castiglione et al., 2023; Del Barrio-Tellado and Herrero-Prieto, 2018; Del Barrio-Tellado and Herrero-Prieto, 2021; Del Barrio-Tellado et al., 2020; Eugenio and Patrizii, 2021; Fernández-Blanco et al., 2019; Hung and Berrett, 2022; Kirchner et al., 2018; Kirchner et al., 2022; Wu et al., 2020)
- museums (Basso and Funari, 2020; Basso et al., 2018; Del Barrio-Tellado and Herrero-Prieto, 2019; Del Barrio-Tellado and Herrero-Prieto, 2022; Del Barrio-Tellado et al., 2023Guccio et al., 2020; Guccio et al., 2022; Kim and

Chung, 2020; Lukáč and Mihálik, 2018; Plaček et al., 2018; Plaček et al., 2021; Plaček et al., 2022; Taniguchi, 2021; Šebová, 2018).

These studies have primarily applied a DEA approach, a method that this paper adopts, to measure efficiency in their respective sectors.

The DEA method allows researchers to select the inputs and outputs that are under the museum's managerial control to produce a ratio that signifies its efficiency. In applying this method to a group of decision-making units (DMUs), one can construct an efficiency frontier highlighting the most efficient firms and the relative efficiency and positions of other implicated firms (Taheri and Ansari, 2013). DEA is particularly suited for the case of museums as firms with multiple outputs and differentiated institutional aims, as one can assign weights to the observed outputs to align efficiency measures more accurately with the firm's intentions that guide its input allocation. These indicators need to be selected carefully or else they are at risk of misrepresenting what they are intended to measure or becoming a goal (Jackson, 1994).

Nevertheless, DEA has some important limitations that need to be noted. Firstly, while the method can assess the efficiency of museums and determine their relative efficiency to one another, thus producing a valuable benchmarking tool, the analysis requires a homogenous group of DMUs. DEA is sensitive to outliers (Del Barrio-Tellado and Herrero-Prieto, 2019), as well as to the weighting that is assigned by a researcher to the inputs-outputs (Taheri and Ansari, 2013). Therefore, it is essential to select a homogenous set of DMUs to analyse, and carefully adopt an appropriate weighting of variables, to not needlessly distort the efficiency measures. Homogeneity in the case of museums refers to the group of museums operating with similar conditions and inputs to produce similar outputs (Basso and Funari, 2004). Carvalho et al. (2014) present another approach in their research on the efficiency of Portuguese museums. They use the museums' budget, weekend opening hours, human resources, and variety of services as criteria by which they clustered their DMUs to ensure homogeneity.

Finally, another limitation of DEA is primarily caused by its narrow scope as a one-stage mode of analysis which does not consider exogenous factors that can affect an institution's efficiency, such as the cultural policy of its region or its geographic location (De Witte and Geys, 2011). Finally, the same authors identify another limitation commonly overlooked by previous studies, namely the lack of attention paid to outputs affecting each other, an impact that can influence the final efficiency measured (De Witte and Geys, 2013). Del Barrio-Tellado and Herrero-Prieto (2019) address this limitation by stating that a "distinction may thus be drawn between programmed outputs and observed outputs" (p. 486). This points to the fact that only some researched outputs, such as the number of exhibitions or other services provided by a museum are directly under their control, while consumer-focused outputs such as visitor numbers are out of the museum's sphere of control, thus necessitating a two-stage analysis of efficiency.

2.2.2 Performance Indicators

Past research on the performance and efficiency of museums, particularly at the very beginning, has used performance indicators (PI) as the primary measurement tool. A performance indicator is used to assess the performance of specific aspects of an organisation and its activities, such as the input and output of various resources, and the impact of projects and programmes. Although they can be used to assess performance and organisational aspects quantitatively and qualitatively, they use a ratio and are inherently numerical (Ames, 1994; Navarrete, 2020). Each PI aims to provide an assessment method that extends beyond efficiency measurement exclusively using the input-to-output ratios. This flexibility allows for the evaluation of an organisation's strengths and weaknesses, as well as its effectiveness (Markić, 2014), an outcome that is not easily captured using standard DEA approaches (Asmild et al., 2007). Although effectiveness and efficiency are strongly linked, they can exist in the absence of the other. Nonetheless, PIs are inherently numerical, regardless of whether they refer to quantitative (i.e., revenue and profit) or qualitative (i.e., educational value) qualities of a museum. This limitation is touched upon by Peter Ames (1994), one of the first researchers to introduce PIs to the museum field. He highlights that, "many, if not most, of the critical qualities of a good museum cannot be measured numerically", as with the case of PIs, a method that cannot provide a comprehensive evaluation of an organisation's performance by itself (Ames, 1994). In other words, organisational effectiveness assessed through PIs does not necessarily indicate that the organisation is operating at its production frontier (Peacock, 2003 in Navarrete, 2020). Further, as with the DEA approach, the final assessment using PIs can be skewed or intentionally manipulated by weighting and PI selection choices made by researchers (Rowe, 2004). Indeed, Jackson (1994) foregrounds that PIs can distort reality due to an organisation's desire to, "appear in the best light". Relying on PIs as a method that attempts to reflect the efficiency and performance of an organisation may also lead to the measurement method becoming an end, rather than a tool for self-assessment. In the case of accountability misalignment between a funding body and a museum, where the demands for accountability exceed the supply, ineffective PIs are likely to be developed (Overman, 2021). These PIs are introduced to appease the unconsidered demands by funding bodies and governments to achieve greater accountability without considering museums' vague priorities and objectives (Overman 2021). Finally, Jackson (1994) highlights that the absence of data, particularly when spearheading the quantification of all aspects of an organisation, risks the non-measurement of qualitative and non-quantifiable values, a critical error in the cultural sector.

One of the first uses of PIs for museum efficiency assessment was presented by Peter Ames (1994) who highlights the museum field's lack of success measurement framework, a tool used across most for-profit industries at the time. The list of indicators established by Ames is meant to provide an assessment of what he believes to be the most important aspects of a museum. The importance of organisational aspects varies across the field, thus necessitating that these PIs are adjusted per institution. This, in turn, can compromise the possibility of comparing multiple institutions' performance using PIs. In any case, PIs, as interpreted by Ames, are meant to be continuously developed by museums and museum professionals who determine indicators, definitions, and ratio ranges for success in their situations. Despite the possibility of continuously perfecting individual PIs, the primary limitation of PIs is their limited scope. Each indicator refers to one aspect of an organisation and although one can establish a collection of multiple PIs, this results in a list of separate assessments of a multi-dimensional organisation at a given time. DEA is like PIs in the sense that it utilises input-output ratios, however, it synthesises its multiple input-output pairs - its PIs - to produce an efficiency assessment of the organisation (Thanassoulis and Silva, 2018).

2.2.3 Balanced Scorecard

The Balanced Scorecard (BSC) method places financial information, such as revenue and profits, in the centre of its assessment of performance. However, it does so by supplementing these metrics with additional metrics from the perspective of various stakeholders involved in or affected by the examined organisation. The complete BSC unites the perspectives of shareholders, customers, employees, and management, with the performance of each measured separately. This allows managers to have a structured overview of the performance of an organisation from various dimensions, while also mapping out its various goals and measures. This is particularly effective for the diffusion of an organisation-wide strategy across all departments and employees, while also preventing an overload of information for managers who remain aware of the most critical performance measures (Kanji and Sá, 2002; Kaplan and Norton, 1992; Quesado et al., 2018). Despite these benefits, the BSC is a heavily managerial-focused tool that can only assist with the performance assessment within an organisation, as opposed to being a comprehensive measurement tool. The nature of BSC necessitates multiple forms of measurement to account for the different goals and perspectives that are included within it. An important limitation of BSC, therefore, is its reliance on an adequate selection of measurement approaches that can reflect the organisation's performance in practice. These must be selected on a case-by-case and organisation-specific basis which is often a complex and arduous process which can influence the ensuing assessment (Quesado et al., 2018).

For museums and the cultural sector, BSC has been employed to assess the performance of museums, such as their effectiveness and success. Zorloni (2016) introduces the BSC approach as an invaluable managerial tool to assess the effectiveness of private art museums. She argues that the method's ability to balance both financial and non-financial metrics, as well as its flexibility to adapt to the needs, wants and context of individual museums. These advantages are not limited to either private or art museums and may be beneficial to the wider field. According to Ilie et al. (2022), the BSC method stands out as an effective tool for assessing museum performance from financial, educational, stakeholder satisfaction and organisational development perspectives. However, the flexibility of this approach is a double-edged sword. The authors note that performance and success should be assessed relative to other similar museums, a process that BSC is incapable of accomplishing due to its flexible use by individual museums with diverse organisational strategies and goals.

Following the overview of various tools for the assessment of museum efficiency, the following section will review the existing body of research that has applied the DEA method for this purpose.

2.3 Literature Review – DEA and Museum Efficiency

The usage of DEA to determine museum efficiency finds its roots in Pignataro's 2002 paper which uses the method to assess the efficiency of Italian museums. He finds that only a few museums are working at an optimal level of efficiency, with most of the inspected museums being inefficient. To reach this conclusion, he used the DEA method along with both financial and non-financial variables as inputs-outputs, such as the museum's budget and visitor numbers. Soon after this, Mairesse and Van den Eeckaut (2002) published their in-depth research on Belgian museum efficiency that further expanded on this line of museum assessment by using an alternative DEA model - the Free Disposal Hull approach (Basso and Funari, 2004). The few assumptions required by FDH allow the researchers to establish three separate models that account for differing outputs based on differing inputs. The authors recognise the multiple dimensions of museums and therefore use three models formed to assess the efficiency of each dimension in the most favourable conditions. Additionally, the authors highlight that using a three-year period in which data was collected further increased their results' robustness and quality. Although a longer period of data collection can smoothen out outliers and non-normal museum efficiency, such as due to sudden prolonged closures, this research will be using a one-year window in which museums are operating in a stable context to capture regular museum activity efficiency. Since Mairesse and Van den Eeckaut's research, most research on museum efficiency has used classical DEA approaches, namely those established by Charnes, Cooper, and Rhodes (1978) (CCR) and Banker, Charnes, and Cooper (1984) (BCC).

More recent studies were conducted by Del Barrio-Tellado and Herrero-Prieto (2014, 2019) who have used the method to non-parametrically gauge the efficiency of regional museums in Spain and their distance from an estimated optimal frontier. Their measurement of efficiency was paired with the establishment of an optimal frontier using cases of best practice in their sample to which other less efficient sampled DMUs could be compared to determine their relative (in)efficiency. The structure of museums as firms with multiple outputs was addressed by the chosen DEA approach which can quantify and aggregate the outputs to determine a firm and industry's production frontier. The authors, however, note that this method is unable to capture the nonmarket in- and outputs of a firm, a common characteristic of public cultural institutions (Del Barrio-Tellado and Herrero-Prieto, 2014). While DEA can address the outputs of museums, Blaug (2001) reiterates that museums' numerous activities and stakeholders, both principals and agents, prevent the definition of one overarching conception of "efficiency" in the museum sector. Therefore, the efficiency captured by DEA is heavily dependent upon the inputs and outputs selected by researchers as they can either be too specific leading to the exclusion of some museums and their activities, or too general and thus not leading to reliable results.

Although the DEA approach is a common method in the analysis of museum efficiency, it is often supplemented with additional methods. A multi-method approach enables researchers to draw more robust and comprehensive conclusions using complementary approaches. Recent studies by Basso et al. (2018) and Basso and Funari (2020) exemplify this approach by carrying out the first joint DEA-BSC two-stage studies on museums. These studies were conducted with the aim of a more well-balanced performance assessment by use of DEA and BSC. These methods allow for the efficiency of distinct goals and aspects of the museum (BSC's "perspectives") to be measured using individual DEA models that provide managers with more specific internal information. The second stage analyses of the studies use a conventional DEA approach to produce a single efficiency value for the organisation to allow for comparisons with other museums. In this study, the DEA approach assumes that the sampled DMUs are operating with variable returns to scale (VRS), also known as the Banker, Charnes, Cooper model (BCC). Operating under variable returns to scale means that changes in inputs do not result in a proportional change in outputs, and vice versa.

Other studies that use DEA have supplemented it with regression analysis (Guccio et al., 2020; Plaček et al., 2018, 2021), Malmquist Index (Pignataro, 2002), Mehrabian, Alirezaee, Jahanshahloo's efficiency ranking method (MAJ) (Taheri and Ansari, 2013) or Analytic Hierarchy Process (AHP) as in the case of Basso and Funari (2020) who develop their DEA-BSC approach even further. The use of DEA in these studies is standardised in the sense that it is a standard DEA process in which researchers select appropriate inputs-outputs which are ultimately synthesised to determine the overall efficiency of an institution. A recent 2019 study by Del Barrio-Tellado and Herrero-Prieto departs from this standardised DEA approach by introducing a two-stage DEA. They argue that not all outputs are under the immediate control of the museum and managers and are inter-reliant, therefore necessitating a separation of outputs by using a two-stage analysis design.

Most of the recent studies on museum efficiency using a form of DEA have been conducted in Spain or Italy, with some of the other discussed papers taking place in Iran, Portugal, and Belgium. This research on the efficiency of Dutch museums using DEA is the first contribution to filling the gap in the literature. Furthermore, it does so by including inputs-outputs related to the widespread digitisation of the museum and cultural heritage sectors in the Netherlands and elsewhere (Navarrete, 2014). Assessing the efficiency of Dutch museums using DEA is both socially and politically relevant as it can lead to inefficient museums identifying areas of improvement and therefore refining their production processes. Furthermore, it is politically relevant as it can enable government funding bodies to more effectively gauge how many resources a museum needs, while taking its institutional mission and focus into account.

3. Methodology

This chapter shows this research's methodology, beginning with the research design in which the aim and general research approach are laid out. Afterwards, it explains the method and sample, as well as how the data was collected.

3.1 Research Design

Despite the Dutch museum field's overwhelming popularity, as indicated by its millions of yearly visitors, there has been little scholarly attention paid to the efficiency of institutions within it. On the other hand, there is a growing body of research on the efficiency of museums in other countries, such as Spain and Italy. Table 1 provides a partial overview of the methodologies of past museum efficiency studies. Considering the lack of comparable research on the Dutch case, this thesis aims to answer the following research question: How technically efficient are Dutch museums?

This explorative study is a quantitative panel study which tracks 17 Dutch museums from 2019 to 2021 along multiple variables. These variables are used in two data envelopment analysis (DEA) models to determine the technical efficiency of the sample under two scale assumptions. The following section will discuss the chosen method, the data collection process and this study's sample.

3.2 Method

Data Envelopment Analysis is a non-parametric measure that allows for the measurement of the relative efficiency of a set of decision-making units (DMUs). In doing so, DEA can establish an efficient frontier, a result which highlights cases of best practice in the sample. For this research, the efficient frontier would highlight the most efficient museums and the inefficient museums' distance to the frontier. DEA uses several selected inputs and outputs to produce a ratio which signifies a decision-making unit's (DMU) technical efficiency. These inputs and outputs are selected to represent the primary activities of museums. More specifically, inputs are selected to represent the resources used by a museum to achieve its organisational mission and goal. Additionally, these inputs are under the museum's direct control allowing for changes to be made in the case of inefficiencies. The outputs produced using the inputs are directly related to the museums' central tasks, such as conservation, restoration, education, research, and accessibility to the public.

Paper	DMUs	Method	Inputs	Outputs
Mairesse and Vanden Eeckaut (2002)	French Belgian museums	FDH (EDH-CRS and NRS) and FDH-RRS	Scientific staff, technical staff, operational budget, security services	Percentage collection inventoried, technical indicator, temporary exhibitions, publications, communication actions, hours open, visitors
Pignataro (2002)	Sicilian museums	DEA (CCR & BCC), Malmquist Index	Admin staff, technical staff, exhibition space (sqm)	Visitors
Basso and Funari (2003)	Italian municipal museums	DEA (CCR & Input-oriented BCC) and FDH	Staff, exhibition space	Full price ticket visitors, reduced price ticket visitors, temporary exhibitions, other activities
Basso and Funari (2004)	Italian municipal museums	DEA (CCR & input-oriented BCC) and cross-efficiency	Staff, exhibition space	Full price ticket visitors, reduced price ticket visitors, temporary exhibitions, other activities
Del Barrio-Tellado et al. (2009)	Spanish museums	DEA (CCR & BCC), Superefficiency	Staff, collection, equipment	Visitors
Taheri and Ansari (2013)	Tehran museums	DEA (output-oriented CCR), MAJ, Full Ranking Method	Space and accessibility index, HR index, Facility index, Introduction index	Visitor index
Del Barrio-Tellado and Herrero-Prieto (2014)	Regional Spanish museums	DEA (CCR & input-oriented BCC), Malmquist Index	Staff, museum size, equipment	Temporary exhibitions, visitors, social impact, impact of collection
Basso and Funari (2020)	Italian municipal museums	Five DEA (BCC), BSC and AHP	Insured Value; Total costs; Constant Input (Dummy); Expenditure; Customer perspective score, internal process perspective score, innovation and learning perspective score, financial perspective score	Visitors, website visits, members, donations, catalogues; Conservation and restoration costs, amount spent on new acquisitions, visitors; Personnel training, sustainability indicators; Ticket income, Sponsorships, donations, public funding, other income

Table 1. Partial overview of previous museum efficiency studies using DEA.

With a non-radial DEA model, input-outputs can be given weights to account for DMUs' differentiated priorities which affect their resource distribution. For example, while one museum may focus on research and publishing articles, another may focus on outreach and educational activities; weights would be distributed differently for these two as one aims to measure them in the best possible scenarios by accounting for their different organisational focuses. To determine the most appropriate weights for individual museums, one would need in-depth knowledge of the DMUs' strategies and their objectives. This could be achieved by consulting relevant stakeholders, such as museum directors and heads of operations who may provide details that are excluded from public documents. This approach, however, is out of the scope of this research.

Instead of using weighted variables, two input-oriented and radial DEA models were used to determine the relative technical efficiency of the sampled DMUs. A DEA model with input-orientation seeks to maximise a DMU's efficiency by reducing its inputs while keeping outputs constant. This orientation is commonly adopted in the literature on museum efficiency (Basso and Funari, 2003, 2004; Del Barrio et al., 2009; Del Barrio-Tellado and Herrero-Prieto, 2014) to suit the conditions of specific case studies. For this research, it appears suitable to use an input-orientation as the pandemic of two of the three evaluated years caused all museums to close their doors for extended periods, while also significantly decreasing physical attendance when allowed to open. The reduced self-generated funds and uncertainty caused by the constantly evolving national and global situation have possibly led to institutions reducing inputs, such as by letting personnel go and not offering certain services and facilities. In addition to the input-orientation, radial DEA models are used as these do not necessitate the use of weights for the variables. When combined with an input-orientation, radial models increase a DMU's technical efficiency by proportionally reducing all inputs (Zhu, 2003).

3.3 DEA Models

The two DEA models with differing assumptions of scale that were used are:

(1) the Charnes, Cooper, and Rhodes (CCR) model that assumes constant returns to scale (CRS)

(2) the Banker, Charnes, Cooper model (BCC) that assumes variable returns to scale (VRS).

The CCR model assumes a linear relationship between inputs and outputs such that an increase in inputs would result in a proportional increase in outputs. Due to this assumption, any inefficiencies captured by the CCR model are attributed to ineffective management or institutional scale. The efficiency measured by CCR is therefore also referred to as the overall technical efficiency (OTE). The BCC model, on the other hand, provides a measure of pure technical efficiency (PTE) which is exclusively concerned with a DMU's resource management. The results of both models were used to determine the scale efficiency scores of the sample (SE). This is accomplished by dividing a DMU's CCR efficiency score by its BCC efficiency score (Banker et al., 1984). SE is a measure that determines whether a DMU is working at the most favourable scale of operations. These three efficiency measures are used by most studies on museum efficiency to account for their various diversified characteristics, such as scale (Del Barrio-Tellado and Herrero-Prieto, 2014).

3.4 Variables

Five inputs and three outputs were selected to reflect the activities of museums (Table 2). Special attention was paid to its digital activities and visitors as these are particularly relevant to museums in the chosen period.

Although past research has used the number of employees as an input to refer to an organisation's human capital (Basso and Funari, 2004; Del Barrio-Tellado and Herrero-Prieto, 2013, 2019; Plaček et al., 2016), this research is instead using the average yearly number of full-time equivalents (FTEs) as an input. FTE refers to the total number of hours that the museum's employees are contractually obligated to work and are paid for. The number of FTEs accounts for different working hours, such as of full-time and part-time employees and the differences between them. Therefore, this variable can more accurately reflect the organisation's available human capital used to produce its outputs throughout the year.

Variables	Description
Inputs	
Full Time Equivalent (FTE)	Average number of FTEs working during each year
Digital Services	Availability of Digitised collections, newsletters, ticket purchase opportunities, museum shop, social media and miscellaneous content (“museum from home” section, stories over objects, interactive content, etc.)
Social Services	Rentable accessibility devices (wheelchairs, crutches, etc.), facilities (accessible toilet, elevators, ramps), complete wheelchair accessibility
Research Services	Availability of library, archive, warehouse, photo services, restoration and conservation studio
Consumer Services	public wardrobe, website, museum shop, café/restaurant, rentable spaces, audio guides
Outputs	
Physical Visitors	Number of physical visitors
Digital Visitors	Number of digital visitors
Publications	Number of research articles, catalogues, guides, newsletters, blog posts

Table 2. Selected inputs and outputs.

The Digital Services input refers to services that do not require a visit to the physical museum. In this sense, this research adopts the distinction between in situ and online services made by Guccio et al. (2020). The focus on digital services provided exclusively by the museum's website and social media falls in line with the output of Digital Visitors. Digital Services refer to digitised collections, publications, newsletters, ticket purchase opportunities, museum shops, social media and other educational and entertainment content. Notably, physical and digital exhibitions are not included as an input as the number of exhibitions does not necessarily form an effective indication of efficiency. In cases of blockbuster exhibitions, museums may opt to schedule or extend exhibitions. This would lead to a lesser number of exhibitions while having stable visitor numbers.

Finally, Infrastructure encapsulates the physical facilities required for a museum to perform its tasks. A modified list of facilities and services was adopted from Del Barrio-Tellado and Herrero-Prieto (2013). The following aspects make up this input: library, archive, warehouse, public wardrobe, museum shop, café/restaurant, rentable spaces, audio guides, accessibility devices and facilities.

The listed inputs are used to produce the following outputs: digital visitors, physical visitors, and publications. No distinction is made between digital visitors who use digital services as a substitute rather than a complement. Throsby and Bakhshi (2013) find that live broadcasted theatre performances lead to greater in-person attendance, a finding that may apply to the case of museums and their digital services. In regular circumstances, this would lead to an overlap between the two variables. However, in the case of this research which primarily accounts for museum operations and physical closures during the COVID-19 pandemic, digital and physical visitors are likely, to an extent, mutually exclusive. Furthermore, previous research on museum efficiency does not sufficiently take the field's digitisation into account. Two papers that stand out in this regard are Guccio et al. (2020) who investigated the effects of ICT on museum efficiency and Basso et al. (2018) who include website visits as an output in their DEA-BSC model. The general lack of attention paid to digitisation is a significant gap, as digitisation within the museum sector opens doors to new audiences and ways of engaging with visitors and forms a large part of contemporary museum strategies (D'Auria, 2022). Publications refer to most written texts that museums publish and include both scholarly research and texts for the public. Finally, Activities is an output that refers to all additional activities that are organised and carried out by museums and their staff. As noted by Basso and Funari (2004), the lack of specific data regarding the different activities leads to the overarching nature of this output instead of separating it into specific sub-groups.

3.5 Data Collection and Sample

The outlined inputs and outputs require a significant amount of data from multiple parts of a museum. As experienced b Basso and Funari (2004), the lack of standardisation of collected and reported data posed a significant barrier to this research's data collection. The sample exclusively consists of public non-profit museums in the Netherlands. As non-profit organisations, public museums are registered as a "public benefit institution" (ANBI) with the Tax and Customs Administration. This designation provides museums with tax benefits as they are not profit-oriented and provide social and economic benefits. As a result, they are required to publish their financial records every year to remain transparent about their use of funds. These reports are accessible to the public. Many institutions go beyond the generic financial forms by voluntarily producing yearly reports on their activities, visitor numbers, successes, research and more. The comprehensiveness and content of these drastically vary from institution to institution, as the supply of information hinges on the museum directors' feeling of accountability (Overman, 2021). The largest differences are between larger museums that tend to publish full-length detailed reports and smaller and mid-sized museums that lean towards providing the minimum legally required information or slightly longer reports. This is potentially due to a lack of funds and employees required to produce a longer report containing data, analysis, design and more.

The final sample consists of 17 museums. The literature on DEA has a range of minimum numbers of DMUs required concerning the number of inputs and outputs. Some scholars suggest using a minimum of twice the number of DMUs as there are inputs and outputs combined (Golany and Roll, 1989; Homburg, 2001) while others recommend at least three times as many DMUs (Banker et al., 1989; Raab and Lichty, 2002). Falling below the minimum of these rules of thumb would further reduce the model's discriminating power. With 17 DMUs and eight variables, the sample is between these rule of thumbs. These museums' reports contained most of the required information, however, in many cases, it was necessary to contact the museum for additional information. This was either due to the institution removing the reports of the previous years, vague language, or not including certain information in the report. This approach is in line with data collection methods of previous research, such as Basso and Funari (2004) who collected data from municipalities and Del Barrio-Tellado and Herrero-Pietro (2019) who conducted surveys and contacted museums directly. In select cases, it was necessary to deviate from established norms by estimating values in place of missing data. This is accomplished by calculating the year-by-year percentage changes for the relevant variable of the other DMUs (e.g., the percentage difference between 2019 and 2020) and then calculating the average percentage change of the whole sample. The affected DMU's available value for the relevant variable is multiplied by the sample's average percentage change to produce an appropriate estimate for the missing value. Two of the 408 data points from the 17 DMUs are the result of this estimation process. Finally, the raw data was normalised using the min-max method to prepare it for the DEA analyses.

3.6 Descriptive Statistics

Table 3 presents descriptive statistics of the data collected on the 17 DMUs. The data shows that during the three-year window, produced publications, on average, remained stable, while the number of physical visitors significantly decreased year-by-year. This can be attributed to the mandatory closure mandate at the start of the COVID-19 pandemic. Considering the physical closures of museums, a small uptick in offered digital services can be seen (2019: 4.7; 2020: 5.1; 2021: 5.2). Despite offering digital services, such as digitised collections and activities, digital visitor numbers initially dropped by 21.02% from 2019 to 2020, before recovering and increasing to 25.24% above pre-COVID numbers in 2021. Considering the rapidly changing situation with museums first being closed in March of 2020, sampled DMUs were possibly not sufficiently prepared or equipped to supply goods and services that could compete with other (digital) entertainment opportunities. Furthermore, prior to the pandemic, Dutch museums generally did not prioritise digital and online approaches to regularly engage with audiences beyond their physical building (Tissen, 2021). The combination of a competitive digital attention economy with countless entertainment options and an underprepared museum field can explain this significant decrease in digital museum visitors. Having had a year of intermittent closures and with no end in sight, Dutch museums may have improved their digital programming and content to attract digital visitors once more. This is a plausible explanation for the recovering digital visitor numbers from 2020 to 2021.

The other inputs regarding the museums' various services (Research, Consumer, Social, Digital) and the employed personnel, remained relatively stable as well. Some of the services that the inputs refer to require a significant investment of time and funds, such as the establishment of a library or archive. Services and facilities such as these may have already been established in the years preceding this research's narrow timeframe or will occur after it. Therefore, there are little changes in these inputs over the three years. The social services variable exclusively addresses physical accessibility provisions and museum attributes such as rentable mobility devices and fully accessible locations. It is possible that museums were not prioritising new accessibility improvements due to a decreasing number of physical visitors and days of operation during the pandemic. Nevertheless, the following section will present the results of the DEA efficiency analyses that address each DMU separately.

The following chapter will lay out and analyse the findings of each of the models.

Variable	Mean	STD	Min	Max
		2019		
Research Services	3.2	1.48	1	5
Consumer Services	5.5	0.6	4	6
Social Services	3.5	1.1	1	5
Digital Services	4.7	0.7	4	6
FTEs	65.81	59.09	10.3	215
Physical Visitors	225,967.00	174,565	38,981	667,477
Digital Visitors	450,865.01	342,476.78	81,600	1,337,685
Publications	30.76	46.51	0	185
		2020		
Research Services	3.2	1.48	1	5
Consumer Services	5.5	0.7	4	6
Social Services	3.5	1.1	1	5
Digital Services	5.1	0.5	4	6
FTEs	65.12	59.89	8.9	219
Physical Visitors	121,151.00	107,863.89	22,939	405,950
Digital Visitors	356,114.94	228,899.57	67,059	804,431
Publications	29.41	44.47	0	161
		2021		
Research Services	3.2	1.48	1	5
Consumer Services	5.6	0.6	4	6
Social Services	3.6	1.2	1	5
Digital Services	5.2	0.5	4	6
FTEs	67.01	59.66	9.49	223
Physical Visitors	98,523.41	68,248.26	26,357	239,057
Digital Visitors	564,653.07	886,805.27	78,000	386,6766
Publications	31.35	45.36	0	164

Table 3. Descriptive statistics.

4. Results

This chapter will present the results of the DEA models, starting with the CCR model. An overview of each analysis can be seen in Table 4.

4.1 Model 1: Assumed Constant Returns to Scale

Assuming constant returns to scale (CRS), eight DMUs were consistently operating at the efficient frontier throughout the period. Excluding these, seven DMUs operated at the efficient frontier for at least one of the years, while the remaining three DMUs were inefficient in all inspected years. The lowest recorded efficiency was reached at 0.41 in 2019 by the Fries Museum **(M5)**. There was a total of 10 to 14 efficient DMUs per year under the assumption of CRS. The following DEA approach which assumes a variable return to scale (VRS), in other words, a non-linear relationship between inputs and outputs, presents a different picture.

4.2 Model 2: Assumed Variable Returns to Scale

Under the VRS assumption, the number of DMUs at the efficient frontier during the pandemic (2020 and 2021) increased by at least two compared to CRS. The largest difference in the number of efficient DMUs was in 2020 with 15 museums at efficient frontier under VRS compared to ten DMUs under CRS. Teylers Museum and Fries Museum (**M3** and **M5)** are the remaining two DMUs that were severely inefficient in all years according to both models, however, to a lesser degree in 2020 and 2021, thus showing marginal improvements. Their efficiency scores under VRS range from 0.52 to 0.62 and 0.45 to 0.83, respectively.

There were at least 13 DMUs that were at the efficient frontier each year. However, the BCC model only led to more efficient DMUs in 2020 and 2021 (18.2 and 50% increases from CCR, respectively). In 2019, 14 museums were efficient under both scale assumptions. The slight uptick of efficient DMUs in 2020 and 2021 can be explained by the BCC model's flexibility when compared to the CCR model which assumes a constant return to scales, regardless of differences in operational sizes. In total, eight DMUs were efficient every year under both CRS and VRS assumptions.

The VRS model substantially differs from the CRS model in many cases, particularly for the 2020 data. The most drastic difference is seen for the 2020 efficiency scores of Fries Museum **(M5)** where CRS records a value of 0.51, highlighting severe inefficiency, while VRS returns a score of 0.83, an increase of 62.75%. This means that the museum can increase by about 17% its output without increasing inputs, to reach its full efficiency potential. The stark contrast between the two scores points to **M5** having effective management of resources and that it is not necessarily operating at the appropriate scale of operations. This is further indicated by its scale efficiency (SE) score of 0.62, its lowest of the three years.

The average OTE of all DMUs expectedly decreased from 0.93 in 2019 to 0.90 in 2020 and 2021. The average PTE was identical to the average OTE in 2019 at 0.93, while the 2020 and 2021 PTE values were 0.97 and 0.94 and thus consistently higher than their respective decreasing OTE values. This indicates that, on average, inefficiencies stem slightly more from inappropriate scales rather than resource management. This is further corroborated by the inverse relationship between PTE and SE in 2019 and 2020 with average PTE values of 0.93 and 0.97 and average SE values of 0.99 and 0.93, respectively. The DEA analyses with the chosen inputs and outputs show that at least 10 DMUs were efficient each year, both under CRS and VRS assumptions. Finally, the SE scores report that at least 10 DMUs were operating at an optimal scale each year.

	CRS			VRS			SE		
Code	**2019**	**2020**	**2021**	**2019**	**2020**	**2021**	**2019**	**2020**	**2021**
M1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M2	1.00	0.79	0.95	1.00	1.00	1.00	1.00	0.79	0.95
M3	0.46	0.59	0.45	0.52	0.61	0.61	0.88	0.96	0.74
M4	0.88	0.88	1.00	0.88	1.00	1.00	1.00	0.88	1.00
M5	0.41	0.51	0.56	0.45	0.83	0.64	0.91	0.62	0.87
M6	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M7	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M8	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M9	1.00	1.00	0.93	1.00	1.00	1.00	1.00	1.00	0.93
M10	1.00	0.92	0.84	1.00	1.00	0.90	1.00	0.92	0.93
M11	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M12	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M13	1.00	0.75	1.00	1.00	1.00	1.00	1.00	0.75	1.00
M14	1.00	1.00	0.63	1.00	1.00	0.77	1.00	1.00	0.82
M15	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M16	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
M17	1.00	0.87	1.00	1.00	1.00	1.00	1.00	0.87	1.00
Average	0.93	0.90	0.90	0.93	0.97	0.94	0.99	0.93	0.95
Total Efficient DMUs	14	10	11	14	15	13	14	10	11

Table 4. Overview of the results.

5. Discussion

This chapter will present an analysis of the results that are considered in relation to the literature on museum efficiency measurement and the circumstances of the chosen time window. Following this, the limitations of this research will be discussed.

5.1 Analysis of Results

The measurement of the efficiency of 17 Dutch museums was conducted using two DEA models: CCR and BCC. Both models reported that a portion of the sample was operating inefficiently, however, they do so to differing degrees. The CCR model functions under the assumption that the DMUs operate with constant returns to scale thus causing an increase in inputs to lead to a proportional increase in outputs. The scale of operations of the sample is non-homogenous, as indicated by the numerous significant ranges of inputs and outputs, such as in 2019 where one DMU employed 10.3 FTEs while another DMU employed 215 FTEs (See Table 3). These large differences in inputs between the sampled DMUs do not necessitate a proportional difference in outputs produced (Jackson, 1988; Del Barrio-Tellado and Herrero-Prieto, 2014). Despite that, the CCR model, which does not account for these differences, reports that a range of 10 (2020; 35%) to 14 (2019; 82%) DMUs operate with technical efficiency each year. Interestingly, while the majority of DMUs are operating at the efficient frontier in 2019, two of the three remaining DMUs are severely inefficient with efficiency scores of 0.41 and 0.46. These two, the Fries Museum and Teylers Museum are relatively similar in terms of inputs and outputs and therefore, CCR efficiency, despite being in non-neighbouring provinces and housing different types of collections (provincial art and objects and art, natural history, and science objects). Furthermore, it is peculiar that despite having fewer FTEs (43.28 versus 45.00) and Research Services (two versus six) as inputs, Fries Museum has welcomed slightly to significantly more physical (145,554 versus 136,738) and digital visitors (398,307 versus 288,828) in 2019. Teylers Museum, however, published 11 texts while Fries Museum only published three texts. The discrepancy in this output has seemingly led to Teylers Museum being more efficient than Fries Museum, despite its other less favourable variables. This implies that, under the radial input-oriented CCR model with no weighting, the difference in publications contributes significantly more to efficiency than other factors.

The following BCC model was employed to provide an overall more accurate and robust efficiency assessment using the selected inputs and outputs. The VRS scores refer to a DMU's pure technical efficiency (PTE), i.e., the allocation of resources and are not swayed by suboptimal institutional scales. On the other hand, CRS scores are a product of managerial strategies and decisions and an institution's scale of operations and therefore indicate DMUs' overall technical efficiency (OTE). In the cases of six DMUs (**M2**, **M4**, **M9**, **M10**, **M13**, **M17)**, inefficiencies can be attributed to suboptimal scales of operations, rather than resource management, as in at least one year their CRS were <1.00, while their VRS scores are 1.00 (Del Barrio-Tellado and Herrero-Prieto, 2014; Jia and Yuan, 2017). Therefore, in the case of these six museums, their inefficiencies can be tackled by either increasing or decreasing the scale of operations to reach an optimal size. Indeed, by accounting for different scales of operations within the sample, the BCC model reported that there were only two inefficient DMUs in the best year (2020) and four in the worst year (2021). This is substantially different from the CCR model which did not account for differences in the scale of operations and as mentioned, reported seven and six inefficient DMUs in 2020 and 2021, respectively.

The BCC model reports efficiency improvements for many DMUs that were deemed to be inefficient according to the analysis using CRS. For **M2**, **M9, M13,** and **M17**, this has led to efficiency in all years, an improvement from having at least one year with inefficiency according to CRS. In 16 of 51 calculated SE scores, however, DMUs were found to be operating at scales that were not optimal given their resources. All cases of suboptimal scales are due to DMUs' scales being too small, rather than too large. Six cases of scale inefficiencies are attributed to two DMUs that are consistently at a suboptimal scale, while the remaining cases are by DMUs that are only temporarily scale inefficient. The two DMUs that are scale inefficient in all years are also inefficient under CRS and VRS, thereby highlighting inefficiencies stemming from suboptimal resource management and scale of operations.

The reviewed time frame primarily takes place during the COVID-19 pandemic during which Dutch museums were ordered to limit the number of physical visitors and the activities they could organize; moreover, for some months, they entirely shut their doors. Data from 2019, a year before the pandemic, can be used as an impromptu benchmark against which the efficiency of DMUs operating in extraordinary conditions in the following two years can be compared. Unsurprisingly, the CCR model records a significant decrease in efficient DMUs in 2020 (2019: 14; 2020; 10), the start of the pandemic, before slightly recovering in 2021 (11). On the other hand, the number of efficient DMUs under the assumption of VRS peaks in 2020 with only two museums being either very (0.61) or somewhat (0.83) inefficient. The influence of operational scale becomes evident in this comparison. DMUs that are efficient under VRS can be inefficient under CRS because the latter assumption does not account for its scale. In comparison to CRS, the additional five efficient museums under VRS are operating efficiently in terms of their input-to-output processes. This VRS efficiency occurs despite operating at a suboptimal scale as indicated by these five DMUs' SE scores ranging from 0.75 to 0.92.

In 2021, there were 13 efficient museums under VRS compared to the 11 efficient DMUs under CRS, with the average VRS score being 0.94, a decrease from the previous year's average of 0.97. On the other hand, the average SE for this year is 0.95, an increase from 2020's 0.93. These results indicate that despite improving scales of operation, the sample DMUs are operating less efficiently, possibly due to new developments from the pandemic and special circumstances. It is evident from the lowest average number of visitors that year that museums were strongly affected by physical barriers to entry, such as mandatory closures or restricted borders (thus fewer international visitors). This resulted in 13 efficient DMUs in 2021 under VRS, the lowest number of the three years.

The number of efficient DMUs for each year and under each assumption is relatively high compared to findings by other researchers in other periods and countries. Although these studies use slightly different inputs and outputs, the number of efficient DMUs they find is noticeably different than presented here. With a sample of 23 museums over two non-consecutive years, Del Barrio-Tellado and Herrero-Prieto (2014) find that 11 DMUs are efficient under CRS, while 13 to 14 are efficient under VRS. Basso and Funari (2004) measure four and five efficient museums under CRS and VRS, respectively, from a sample of 15. Finally, in a study on six museum clusters comprising 76 museums, Del Barrio-Tellado et al. (2009) find a total of 17 efficient DMUs under CRS and 31 under VRS. The proportion of efficient DMUs found in this research is markedly higher than those of the studies above. This is either due to different inputs and outputs, weights, time periods, spatial situations, or organizational and management strategies.

The lack of the *Activities* output (workshops, seminars, tours, events, etc.) may have led to skewed results as the only core museum output included in the research as an output is *Publications.* The number of FTEs employed by museums also includes personnel responsible to produce the *Activities* output. The inclusion of these employees as an input without addressing their output is likely to have influenced the calculated efficiency scores. The sampled DMUs have various organisational priorities, with four having a significantly larger number of publications than the rest, indicating a potential research focus. Of these four, three were at the efficient frontier throughout the three years and under both CRS and VRS assumptions. During the three years, the fourth was efficient under VRS while it was at 0.79 to 0.95 efficiency under CRS. The models may inflate these DMUs' efficiency scores and place most of them at the efficient frontier because their primary institutional focus – *Publications* – was assessed and not *Activities,* an output which may have decreased their overall efficiency. This could have contributed to the higher number of efficient DMUs in the sample.

The time window and the relatively small size of the Netherlands could have also played a role in the high number of efficient DMUs. For two of the three investigated years, the sampled museums were affected by the COVID-19 pandemic and associated government-imposed measures. Only one year's collected data (2019) were free of exogenous shocks and therefore presents a limited view of the sample's efficiency during regular operational circumstances. Although the number of efficient DMUs in this case is still relatively high when compared to other studies, it is a less striking difference. Furthermore, the findings of one year can only provide limited evidence of a museum's true efficiency as it is not contextualised by more years of data to determine if it is an outlier. The pandemic in the following two years affected the whole Dutch museum field identically due to blanket government measures that did not include exceptions to specific museums. Although the geographic location of Dutch museums influences the number of physical visitors they attract (de Graaff et al., 2009), these differences were flattened by measures that led to museums' temporary closures. A decrease in self-generated funds from tickets and a decrease in organised activities have also affected the entire field identically due to mandatory closures. The shifting baseline of efficiency and museum activities, therefore, can contribute to a significantly higher number of efficient DMUs in 2020 and 2021. Despite inputs remaining largely unchanged and outputs significantly decreasing compared to 2019, the average number of efficient DMUs during the pandemic years remained stable. It is plausible that the relative efficiency and high number of DMUs at the efficient frontier in 2020 and 2021 are largely determined by a uniform decrease in efficiency caused by the pandemic. Therefore, while the DMUs have generally decreased in efficiency, as indicated by the stable inputs and decreasing outputs, their relative efficiency to each other remained stable or increased, rather than decreased, compared to 2019.

To answer this thesis' research question, the results and discussion indicate that during regular operational circumstances (2019), (sampled) Dutch museums are generally efficient with 14 of 17 DMUs being efficient under CRS and VRS. On the other hand, two of the three inefficient DMUs are severely inefficient. This highlights them as outliers in the mostly efficient sample. While these two DMU were severely inefficient, the remaining and third inefficient DMU in 2019 was slightly inefficient before reaching efficiency in 2021. In 2020 and 2021, the number of efficient DMUs under CRS is the lowest at 10 and 11, respectively. Under VRS, however, the number of efficient DMUs peaks at 15 in 2019 and then decreases to 13. The contrast between CRS and VRS efficient DMUs points towards inefficiencies stemming from the scale of operations not being ideal. Neither efficient nor inefficient DMUs could be characterised by a shared region or type.

5.2 Limitations and Future Research

Some aspects of this research influence the implications that can be drawn from the results. As with previous studies using DEA to measure the efficiency of museums, this research is primarily limited by the available data. The chosen inputs and outputs and studied sample were affected as a result.

This research was initially based on the methodology developed by Del Barrio-Tellado and Herrero-Prieto in their 2014 study on regional museums in Spain. While the selected inputs and outputs reflected the core museum activities at the time, some modifications were made. To better reflect the increasing importance of digitisation within the (Dutch) museum field and its prioritisation prompted by physical closures in 2020 and 2021, two variables were added: digital services as an input and digital visitors as an output. With these additions, there were a total of four inputs and five outputs. Following the rules of thumb regarding the minimum number of DMUs in relation to the number of variables, it would have been necessary to have between 18 and 27 DMUs for the model to have sufficient discriminatory power. The state of data reporting, either through direct contact with museums or by their yearly reports, however, prevented the collection of a sufficient number of complete data sets. Dutch non-profit museums are only required to publicly declare their financial situation, while the data required for the initial DEA model can be shared voluntarily. To address this, the input and outputs had to be modified or removed to account for the available data.

Information on the physical size of exhibition space and museum buildings was not readily available from any public source or through direct contact with museums. These aspects were accounted for by the input *Size* by Basso and Funari (2004) and Del Barrio-Tellado and Herrero-Prieto (2014). In combination with *Size*, the latter authors used the *Equipment* input as indicators of the museum's capital resources. The size of the collection could have been an alternative input to indicate the museum's capital and scale of operations, however, these numbers are not readily available either. To partially address the museum's capital resource as a significant input, the *Equipment* input was split into three portions to differentiate equipment categories that contribute to different types of museum activities. These inputs form the only reference to the physical museum and its capital resources and do not account for physical size differences that may also influence other outputs such as the number of physical visitors.

A few studies have explicitly included, as an output, the organisation of public activities, such as workshops, guided tours, open days, lessons, conferences, festivals, and more. In particular, the studies that have included all or some of these types of activities in their research as an output are Mairesse and Eeckaut (2002), Basso and Funari (2004), and Del Barrio-Tellado and Prieto-Herrero (2014, 2019). The organisation and execution of these sorts of activities require both funding and human capital. Due to the lack of standardisation of data collection and reporting by museums, as experienced in this research, it is unsurprising that only a handful of efficiency studies have included public activities as an output. This is further exacerbated by this study's three-year window, as some museums had altered their data collection and reporting strategies in-between years. Basso and Funari (2004) reiterate this difficulty as well and highlight that their output on public activities could not be split into specific categories (educational, academic, entertainment, etc.) due to limitations imposed by museums' own data collection procedures. Despite this, they have included one output aggregating all types of public activities as they did not consider it to be a significant output in their sample. Many potential museums for this thesis collected data on their public activities in a similar unstandardised fashion to those of Basso and Funari's 2004 study. The number and type of activities that could have been collected varied to a great extent amongst the current sample. Potential and sampled museums provided either a sum of all activities (tours, events, workshops, etc.), the number of some organised activities, or nothing. Therefore, to represent the sample on equal terms, this output was removed from the model. It may have been possible to collect this data commercially, such as in the case of Plaček et al. (2016) who did so to circumvent similar data collection barriers, however, this was not a possibility for this research. Future research could take this approach or directly work with museums to collect such data, as this output forms an important aspect of museum operations. Collaborating with museums to retrieve data would also allow one to have a better understanding of what their organisational focuses are. This information can inform the weighting distribution of non-radial DEA models that would supply more accurate information on each DMU's efficiency. In this research, CCR and BCC models are not able to account for efficiency differences between DMUs that have the same CRS or VRS efficiency scores. Each year there were a majority of efficient DMUs, and likely to differing extents. The two DEA models' inability to rank score-sharing DMUs is a further limitation of this research's methodology.

Following the changes to the initial variables, it was possible to collect nearly complete data on 17 DMUs resulting in 408 data points of which two were estimated using the existing data. In relation to the number of variables, this sample is located slightly above the lower boundary for the model to retain its discriminatory power. Furthermore, the sample size limits the explanatory power of the implications drawn from results vis-à-vis the Dutch museum field. Future research should address the data collection difficulties that affected past and current studies to allow for a greater sample size. This would enable stronger generalisations and implications to be made from the results.

6. Conclusion

This exploratory research set out to assess the technical efficiency of Dutch museums between the years 2019 and 2021. This thesis has discussed the origins of performance measurement in the cultural sector and the challenges posed by the ambiguous value of culture. It was determined that the primary driving force behind the structured measurement and quantification of cultural organisations' activities came from governments around the world. Relevant to this research is that the Netherlands began using measurement-based policies in the public and cultural sector in the 1970s. The measurement of performance allowed governments to hold the recipients of significant subsidies and funding accountable for their efficient and effective use. This motivation was borne out of governmental austerity measures introduced to tackle the financial hardships that many countries faced around the world, particularly following the financial crisis of the 1980s.

Cultural goods and services are characterised by multiple non-market values, such as artistic and aesthetic value, and conventional valuation efforts that only account for economic value are not sufficient. Unsurprisingly, cultural professionals and organisations expressed reservations and resistance to the quantitative measurement of their work, especially considering its potential in determining future subsidies and supply of cultural goods and services. As highlighted in the introduction, this is the first study to investigate the efficiency of the Dutch museum sector. This is particularly surprising because of the long-standing use of measurement-based policies and performance indicators in the Dutch cultural sector. To assess the efficiency of Dutch museums, data from 17 Dutch museums were collected from their yearly reports and through direct contact. The final dataset contained 408 data points on the sample's inputs and outputs. This data was used in two DEA models assuming either CRS or VRS. These two measures allowed for a third measurement to be calculated: SE. The results of these three measures show that most Dutch museums are operating efficiently in the investigated years and using this set of variables. However, only one of the three years (2019) represents a normal operational environment, as museums were affected by measures to curb the pandemic of the following two years. These measures influenced their inputs and outputs, thus leading to efficiency results that may reflect the abnormal circumstances. Despite these circumstances, the DEA models represent the relative efficiency of the sampled museums, therefore how they navigated the government measures and pandemic that levelled the field and smoothed differences between museums.

In 2019, 14 museums were efficient under CRS and VRS. A year later, there were ten efficient museums under CRS while there were 15 under VRS. Finally, in 2021 there were 11 efficient museums under CRS and 13 under VRS. A general finding, therefore, is that in all years and under both scale assumptions, most sampled Dutch museums were operating efficiently. Under this thesis' models, this finding may apply to the entire museum field. Although museums faced intermittent closures, limited visitors, and other measures to curb the pandemic, they were surprisingly operating efficiently for the most part. This can be attributed to the DEA approach which measures relative efficiency and the pandemic equalising the differences between the museums. Therefore, while the sampled museums' inputs remained mostly unchanged, their outputs decreased for the most part. These decreases in outputs occurred to similar extents for each museum causing most museums to be seen as operating efficiently in 2020 and 2021, despite lower outputs than a year before. There were only three museums that were consistently inefficient under CRS and VRS throughout each year.

It must be noted that these findings are primarily shaped by the chosen inputs and outputs. The efficiency scores of the sampled museums can change during the same years if assessing them according to a different set of variables. The most notable limitation is the absence of a variable accounting for the activities, such as workshops and tours, organised by the museums. This is attributed to the lack of standardised information collected and provided by museums, a common limitation highlighted in other reviewed efficiency studies. Furthermore, the chosen methods do not allow for the differentiation of efficient museums as there are likely differences in the extent to which each institution is efficient, despite having a score of 1.00 according to the models. Finally, the radial DEA models do not account for each institution's priorities which shape their resource allocation decisions. Future research on the efficiency of Dutch museums should take these limitations into account by supplementing the DEA methods with a full ranking method, assigning appropriate weights to the variables and accounting for all activities that characterise museums.

To conclude, the conducted research and discussion have sufficiently tackled the primary research question regarding the technical efficiency of Dutch museums. The analysis has established that most Dutch museums are operating efficiently throughout the assessed years according to both DEA models. Both the developed methodology and the ensuing results can have implications for Dutch cultural policy. For one, this research's results may have implications for the funding opportunities for the identified inefficient DMUs, as governing bodies may choose to further evaluate them in terms of performance and operations. On a larger scale, the tested methodology can feasibly provide a foundation for governing and funding bodies to evaluate museums and other cultural organisations as part of their assessment and accountability processes. However, future research should address the limitations of this research by evaluating DMUs throughout a larger time window characterised by regular operational circumstances for museums. For this research, the lack of available data prevented the assessment of the sampled museums using a larger time window. A larger timeframe and data from after COVID-19 would enable the use of new methods to more accurately assess museum efficiency and the disruption caused by the pandemic.

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