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HIGHLIGHTED PAPER

Content analysis in local government accounting – a literature review and empirical insights

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ABSTRACT

This study addresses a gap in local government research by advocating for the adoption of computerised content analysis methods to analyse public service accounting texts. Despite the significant volume of textual data produced by local governments – such as financial statements, budget reports, and policy documents – traditional manual content analysis methods have limited researchers' ability to harness these resources effectively. By employing tools such as the Linguistic Inquiry and Word Count (LIWC-22) software and custom Python code, this study highlights the potential of computerised approaches to enhance the depth, efficiency, and rigour of content analysis in the public sector.

Using annual budget reports from eight Irish local governments as empirical examples, the study applies both standardised and customised analytical techniques to assess textual complexity, readability, sentiment and thematic trends. The findings highlight notable differences in text characteristics between urban and rural local governments and reveal temporal shifts influenced by broader policy initiatives, such as climate action planning. Additionally, the study demonstrates the advantages of combining off-the-shelf tools with tailored programming to achieve more comprehensive insights, particularly in capturing nuanced linguistic patterns.

This research illuminates the value of computerised content analysis in public sector accounting research. While focusing on budgetary documents, the methods described have broader applicability to other public sector texts, paving the way for innovative research approaches in public governance and administration.

Keywords: Local government; Accounting; Content analysis.

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Análise de conteúdo na contabilidade da administração local – revisão da literatura e observações empíricas

RESUMO

Este estudo aborda uma lacuna na investigação sobre a administração local, defendendo a adoção de métodos informatizados de análise de conteúdo para analisar textos contabilísticos dos serviços públicos. Apesar do volume significativo de dados textuais produzidos pelas autarquias locais – tais como demonstrações financeiras, relatórios orçamentais e documentos relacionados com políticas –, os métodos tradicionais (manuais) de análise de conteúdo têm limitado a capacidade dos investigadores para aproveitarem eficazmente estes recursos. Ao utilizar ferramentas como o *software Linguistic Inquiry and Word Count* (LIWC-22) e código *Python* personalizado, este estudo destaca o potencial das abordagens informáticas para melhorar a profundidade, a eficiência e o rigor da análise de conteúdo no setor público.

Utilizando relatórios orçamentais anuais de oito autarquias locais irlandesas como exemplos empíricos, o estudo aplica técnicas analíticas normalizadas e personalizadas para avaliar a complexidade textual, a legibilidade, o sentimento e as tendências temáticas. Os resultados destacam diferenças assinaláveis nas características textuais entre as administrações locais urbanas e rurais e revelam mudanças temporais influenciadas por iniciativas políticas mais amplas, como o planeamento de ações climáticas. Além disso, o estudo demonstra as vantagens de combinar ferramentas prontas a utilizar com a programação personalizada para obter informação mais abrangente, nomeadamente para a captura de padrões linguísticos matizados.

Este trabalho demonstra o valor da análise de conteúdo informatizada na investigação contabilística do setor público. Embora se concentre nos documentos orçamentais, os métodos descritos têm uma aplicabilidade mais ampla a outros textos do setor público, abrindo caminho a abordagens de investigação inovadoras no âmbito da governação e administração públicas.

Palavras-Chave: Administração local; Contabilidade; Análise de conteúdo.

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1. Introduction

Local governments produce a vast array of textual data, including financial statements, budget reports, policy documents, and other official communications. However, much of this rich data remains underutilised, largely due to the labour-intensive nature of traditional content analysis methods. While manual content analysis has served as a valuable tool in understanding various dimensions of governance and accountability, the use of computerised methods offers a transformative potential (Beattie et al., 2004; Vourvachis & Woodward, 2015). The primary objective of this study is to showcase how computerised content analysis methods can be applied to accounting-related texts published by local governments. More specifically, this paper uses the Linguistic Inquiry and Word Count (LIWC) and Python coding to analyse the prevalence of certain word types, evaluate readability and assess trends in specific words. By leveraging technologies such as Natural Language Processing (NLP) and advanced readability metrics, computerised content analysis offers potential for researchers to process large volumes of text efficiently, uncovering patterns, sentiments and themes that would otherwise be obscured. This study addresses a significant gap in the use of computerised content analysis methods in local government research, highlighting its potential for analysing public service texts. By advocating for the adoption of these such tools, we argue that computerised content analysis can greatly enhance the depth, efficiency, and rigour of research in this domain.

This paper positions computerised content analysis as a methodological advancement for local government research, particularly in the analysis of publicly available texts like budget documents. Building on existing literature, this study demonstrates how tools such as LIWC and Python coding can yield rich empirical insights, which may advance both theoretical and practical understanding. By utilising Irish local government annual budget reports as empirical examples, this paper reveals the potential of computerised content analysis methods to enhance public service research strategies.

The remainder of this paper is structured as follows. The next section reviews literature on content analysis methods. This is followed by the study's context, data sources and the computerised content analysis methods used to analyse the data. The findings are then presented and discussed. Some concluding comments, including limitations of the study and areas for future research, complete the paper.

2. Content Analysis Methods

Content analysis is a widely used research method in a variety of settings e.g. psychology, communications, anthropology, organisation studies (Vourvachis & Woodward, 2015) and in accounting (Moreno et al., 2019; Steenkamp et al., 2007). However, this research approach is not commonly utilised in local government accounting studies, being more commonly applied in research focused on central government contexts. This is surprising, considering the role local government plays in communities and the content produced by local governments. A brief review of literature on content analysis research relevant to this paper follows.

Content analysis involves systematically and consistently examining documents and texts, whether in print or visual form, with the aim of categorising their content based on specific, predefined categories. Krippendorff (1980) defined content analysis as a research method for making replicable and valid inferences from data according to its context. While there is an element of subjectivity involved with the application of content analysis, it can enable researchers to go behind the text as presented to make valid inferences about hidden or underlying (and possibly unintended) meanings and messages of interest. In the social sciences, where meanings and interpretations are central to the understanding of social phenomena, content analysis has been lauded as an important research technique (Krippendorff, 2004).

Beck et al. (2010) provided a comprehensive review of content analysis techniques in accounting research. They identified two broad types: mechanistic and interpretative. The mechanistic approach primarily involves quantifying textual elements, such as counting words, sentences, page proportions, and disclosure frequency. Examples include O'Donovan (2002) and Unerman (2000), who examined corporate social responsibility disclosures in annual reports. The interpretative approach, by contrast, focuses on analysing narratives to capture meaning by breaking down texts into components and discussing them (e.g., Quinn et al., 2023). Content analysis is widely used in social and environmental reporting studies within accounting research. A substantial body of literature exists on corporate social, ethical, and environmental reporting, dating back to early work by Guthrie & Parker (1990).

In recent years, the availability of advanced software tools has significantly reduced the labour-intensive nature of content analysis. Furthermore, the increasing availability of data in digital formats has made it easier to conduct computer-assisted analyses. Within the accounting literature, company annual reports are recognised as widely read documents, with particular emphasis on the chair's statement (Courtis, 2004; Fanelli & Grasselli, 2006; Jones, 1988; Moreno et al., 2019; Subramanian et al., 1993), which has frequently been used as a primary data/information source for content analysis studies. This method has been applied to a variety of accounting topics, including sustainability (Chiba et al., 2018), heritage assets (Ferri et al., 2021), fisheries (Quinn et al., 2023), slavery (Christ et al., 2019), environmental disclosures (Cho et al., 2010), impression management (Brennan et al., 2009), corruption (Blanc et al., 2019), and gender equality (Al-Nasrallah, 2023).

Some studies have applied similar methods to local government documents, albeit less extensively. Early research in this area often relied on manual content analysis techniques, developing classification systems to summarise the content. For example, Ho & Ni (2005) analysed the budgetary documents of cities, identifying over 4,800 performance measures and categorising them into eight distinct groups. Similarly, Stanley et al. (2008) examined legally required community financial reports in Queensland, Australia, employing an index method, classification criteria, weights, and scoring methodologies. Marcuccio & Steccolini (2009) used a manual approach to study performance reporting in Italian local governments, concluding that the nature of authority activities influenced report content. These studies, predominantly employing manual methods, reflect the timeframe and specific objectives of the research. Most have relied on thematic content analysis, classifying themes or categories in a qualitative manner. However, manual content analysis becomes increasingly challenging when dealing with large volumes of data or longitudinal studies. Examples of longitudinal content analysis of private sector organisations include studies by Moreno et al. (2019), van der Steen et al. (2022), and Quinn et al. (2023), all of whom have used computerised methods to some extent. Such studies highlight the potential for a similar longitudinal approach in local government research.

Turning to more advanced methods of content analysis in local government research, studies employing a semantic approach appear particularly scarce. A semantic approach focuses on the context of word usage and text structure to uncover relationships and infer meaning from the text, typically leveraging software with Natural Language Processing (NLP) capabilities. It is notable that such methods are rarely applied to local government documents, given their potential to signal intent, employ cautious or politically charged language (Resche, 2015), or serve as tools for legitimising actions. A small number of recent studies have used a semantic approach in research with a similar context to here. Trivellato et al. (2023) studied leadership and success in networks of public, private and non-profit organisations in Northern Italy, using a manual coding of emotion words, i.e. sentiment of words. Their manual study acknowledged difficulties in determining emotion words. However, software like LIWC, for example, includes dictionaries for positive and negative emotion words, which could aid in such analyses.

Continuing the exploration of semantic approaches in analysing local government documents, Roundy et al. (2023) studied the annual financial statements of over 400

US cities and counties and is closely aligned with the present research. Using LIWC software, they identified complex words as an input to a variant of the Gunning Fog Index, a readability metric. Their analysis examined correlations between report complexity – measured by the length of the annual report and the Gunning Fog Index – and variables such as organisational size, complexity, and financial performance. Their findings suggest that poor-performing local governments produce less understandable annual reports. However, unlike this study, Roundy et al. (2023) did not utilise LIWC variables to assess the text of their sample reports directly – only to capture document length –leaving an area of inquiry that the current research seeks to address.

3. Study context, data sources and method

3.1. Irish local government context

Some content on local government in Ireland is useful before we explain our data sources and methods. The Minister for Housing, Local Government, and Heritage oversees all local government in Ireland, holding each city or county accountable to the central government. Irish local government provides public services such as housing, planning, roads, environmental management, recreation, economic and community development, fire services, and maintaining the electoral register. Each local government is led by a Chief Executive (CE) (Griffin-Bertz, 2018). The CE's role is unique compared to other local government systems due to their significant independent decision-making powers (Boyle, 2014). The CE's role is independent from party politics and local influences, and has a standard contract of seven years, extendable by three years (Boyle, 2014). As Boyle (2014, p. 9) notes, "the manager works with, and for, an elected council" and the "financial independence of councils is very limited".

The Local Government (Ireland) Act 1898 established counties as the main administrative unit of Irish local government (Forde, 2005, p. 137). After gaining independence in 1922, Ireland redesigned its local government system to move away from British models (Roche, 1982). The post-1922 reforms introduced city and county management, starting with the Cork City Management Act in 1929, followed by Dublin in 1930, Limerick in 1934, and Waterford in 1939 (Boyle et al., 2003; Haslam, 2001). The County Management Act of 1940 extended this system to all counties (Boyle et al., 2003; Haslam, 2001). Sheehy (2003) explained how the County Management Act (1940) distinguishes between reserved and executive functions. Reserved functions, which include adoption of budgets, approving development plans, and adjustments to local property taxes, are handled by elected council members who represent their constituents, while executive functions, managed by the CE, cover day-to-day operations (Asquith & O'Halpin, 1998). Examples of executive functions include staff appointments, granting planning permissions, and housing allocations (Boyle et al., 2003, p. 27). Irish local government is notable for its strong management focus and limited range of functions compared to other countries, where local governments often handle education, policing, health services, and social welfare (Callanan, 2003). Dollard (2003) notes that Irish local government expenditure is low compared to other European countries due to this limited-service range. Additionally, since the abolition of domestic property rates in 1978, local governments have had limited tax-raising powers (Boyle et al., 2003).

Under the Local Government Act (2001), Irish local governments must prepare annual budgets – the budgets are thus a management control task and a statutory duty. Their income comes from central government funding and locally generated revenue, the latter being typically 30-50% of their income. The finance team of each local government presents the budget to elected representatives for approval in November/December, aiming to produce a balanced budget for service delivery. The approved budgets, which include a report by the CE, are made public via the local governments' webpages.

3.2. Data sources and method

This study demonstrates how computerised content analysis methods can be applied to local government budget documents, focusing on the rich potential of publicly available texts for research. Irish local governments typically produce and publish three key annual documents: the Annual Report, the Annual Financial Statements, and the Budget. Among these, the Budget documents are the primary data source for this study. Eight local governments were purposively selected to reflect diverse demographics (urban, rural, and mixed urban-rural) and regional representation across Ireland. The selected local governments, listed alphabetically, are Cork City, Dublin City, Fingal, Galway City, Limerick City & County, Monaghan, Roscommon, and Tipperary. Table 1 provides details of these local governments. The combined revenue expenditure of the selected local governments for the most recent financial year analysed (2023) was €2.43 billion. Budget files, generally accessible on the websites of each local government, were downloaded for analysis. Efforts were made to maximise the number of documents obtained, resulting in a dataset spanning 12 years (2012-2023) for most local governments, with Tipperary being an exception (2015-2023, nine years). In total, 93 Budget documents in PDF format were collected. While these documents are rich in numerical data, which is less suited for content analysis, they also include textual elements such as the Chief Executive's (CE) Report. This CE's Report is the key textual data source for this study. Relevant sections were extracted and saved as PDF files for further analysis.

Table 1. Detail of local governments analysed

Local government	Demographic	Population (Census 2022)*	Expenditure budget for services in 2023, €m	Expenditure per head of population, €
Cork City	Urban – south	224,004	268.0	1,196
Dublin City	Urban – east	592,713	1,130.0	1,906
Fingal	Rural/urban – east	330,506	333.7	1,010
Galway City	Urban – west	84,414	113.3	1,342
Limerick City & County	Urban/rural – west	209,536	231.5	1,104
Monaghan	Rural – north	65,288	80.0	1,225
Roscommon	Rural – west	70,259	72.1	1,026
Tipperary	Rural – south	167,895	205.0	1,221

*Source: http://data.cso.ie , Census 2022, table FY003A
Note: the published 2023 budget expenditure for Limerick City & County was €905.6 million. This included an amount of €674.1 million allocated to run the Housing Assistance Programme shared services centre (SSC). Given this SSC cover all local authorities, the amount is excluded above.

As mentioned earlier, the primary objective of this study is to showcase how computerised content analysis methods can be applied to accounting-related texts published by local governments. Two analytical approaches were employed: (1) using off-the-shelf software tools and (2) developing customised code in Python. These methods complement each other by offering both standardised and tailored insights into the texts.

The first method utilises Linguistic Inquiry and Word Count version 2022 (LIWC-22), a tool designed to analyse texts based on predefined language categories. LIWC-22 offers 110 variables for analysis, of which eight were selected for this study: word count, analytic, clout, tone net, work, money, focus present, and focus future. Table 2 outlines the selected variables, their measurement details, and a rationale for their inclusion. The second method uses customised code written in Python. One of the present authors has general coding expertise. Using these skills and the assistance of Microsoft Co-Pilot (artificial intelligence)[i], programme code was developed for two tasks. The first Python code task was to assess the readability of the texts. Readability can be measured using the Gunning Fog Index and the Bog Index, both of which were calculated using Python code. The code calculated the readability formulas, after processing the text using the Natural Language Toolkit (*nltk*) package in Python. The *nltk* package processes text to identify sentences, count words, measure word length, and perform other linguistic analyses. The Gunning Fog Index is commonly used to assess readability of general texts. Per the Gunning Fog Index, texts for a wide audience generally should have an index less than 12. An index over 17 is equated to the reading level of a college graduate – see Gunning (1969). A variation of the Gunning Fog Index was used by Roundy et al. (2023) in a local government context. The Bog Index is designed for more business specific texts. It captures almost all the Securities and Exchange Commission's (SEC) plain English guidelines for corporate reporting and is recommended for assessing readability in corporate financial disclosures (Bonsall et al., 2017). The Bog Index score can be interpreted as follows – 0-20 = excellent; 21-40 = good; 41-70 = average; 71-100 = poor; 101-130 = bad; 131-1000 = dreadful. The budget text analysed in this paper is arguably more business than general in nature.

Furthermore, Python code was also used to analyse the prevalence of specific words related to sustainability and climate concerns within the CE's Reports. Any words could be chosen; we use words related to sustainability and climate concerns solely as an example. Keywords such as "recycle," "carbon," "circular," "climate," "emissions," "renewable," "sustainable," and "waste" were selected. The *nltk* package's word stemming feature ensured variations (e.g., "recycle," "recycles," "recycling") were captured. By analysing texts over a 12-year span, this method efficiently provides insights into trends in sustainability-related discourse within local government budgeting.

The combination of LIWC-22 analysis and custom Python coding highlights the flexibility and depth of computerised content analysis. LIWC-22 provides standardised metrics, while custom coding enables tailored investigations, such as readability assessments and keyword trend analysis. Together, these approaches demonstrate the potential for researchers to extract meaningful insights from accounting-related texts like Budget documents. While this study focuses on the CE's Reports in annual Budget documents, the methods described can be extended to other textual data produced by local governments worldwide.

Table 2. LIWC-22 variables used

Variable	LIWC-22 abbreviation	LIWC-22 entries per variable	Measurement/description/logic for inclusion
Word count	WC		Total word count. Measure of complexity. Longer is typically equated to more complex. Used to assess complexity of document.
Analytic	Analytic		Increasing scale from 0 to 100. Metric of logical formal thinking. Local government budgets are typically restricted and may have to allocate funds to several available options, thus an analytical approach may be expected.
Clout	Clout		Increasing scale from 0 to 100. Language of leadership, status. The budget text is approved by the local government CE in an Irish context, who can be construed as a position of status.
Tone net	Tone_pos/ Tone_neg	2,550	% of total words. A measure of the sentiment of words, being positive or negative. Both positive and negative are combined as one measure. Included to determine if emotional sentiments are prevalent in budget text.
Work	Work	547	% of total words. Words associated with work. Variable included as a budget can be thought of as a plan of work to be done.

Variable	LIWC-22 abbreviation	LIWC-22 entries per variable	Measurement/description/logic for inclusion
Money	Money	281	% of total words. Words associated with money and finance. Variable included as a budget is typically expressed in monetary values.
Focus present	Focuspresent	373	% of total words. Words associated with the present. Variable included to determine if language is attempting to distract from future plans, which is what a budget should be about.
Focus future	Focusfuture	138	% of total words. Words associated with the future. Given a budget is a plan for the future, future focused words are to be expected.

4. Empirical insights

The findings from the analysis are presented in the following two sections. Insights from LIWC are presented first, followed by insights based on the customised code.

4.1. Insights from LIWC

The complete results from LIWC-22 by local government and year can be seen in Table 3. Each variable result is presented and then discussed individually below. Where prior relevant literature exists, the findings are related to it.

As noted in Table 2, word count is a measure of the complexity of a text. Typically, higher word counts are associated with greater complexity and reduced readability – see Loughran & McDonald (2016). The analysed texts reveal an average word count of 3,275 words, although as can be seen in Figure 1, the word count varies by local government. Roundy et al. (2023) noted an average word count of just over 29,300 for the complete annual reports of over 300 cities in the United States. Comparably, the word count here seems reasonable given the CE's budget report is less extensive than an entire annual report. The lowest average word count is attributed to Monaghan at 1,266 words, the highest average word count being that of Limerick City & County at 5,179. Interestingly, the urban local governments tend to have a greater word count, which likely reflects the more complex nature of planning expenditures for more populated local government areas. Looking at Figure 1, the word count in Galway City portrays a peak in 2022, at 13,088 words (see Table 3). This peak is an outlier, which prompts further examination. A more detailed analysis of the 2022 CE's budget report for Galway City reveals no changes of CE – Moreno et al. (2019) suggested a change of manager/leader in an organisation can affect the nature of the texts produced. The analysis does reveal a substantial amount of comment on the unwinding of various measures implemented by Galway City to assist citizens and businesses during the COVID-19 pandemic. Another local government worthy of comment is Limerick City and County. This local government is an outlier in that the word count has increased since 2016. A closer read of the CE's budget reports since 2016 reveal additional and increasing commentary on the Housing Assistance Payment (HAP) Transactional Shared Service Hub. The HAP is a subsidy given to citizens to help pay rent to private landlords where the local government cannot provide social or affordable housing. The Shared Service Hub opened in Limerick in 2016 and provides services to all Irish local governments on HAP transactions.

As noted in Table 2, the LIWC-22 variable *analytic* is a metric of logical formal thinking. It is measured on a scale from 0 to 100, with 100 being highly analytic text content. Table 2 also proposes that a local government is typically limited in what it can do by its budget constraints. As a result, any local government may have to choose from several available courses of action and as a result an analytical approach is to be expected, which should in turn be expressed in texts related to budgets. As can be seen in Figure 2, all analysed local authority budget reports convey a high presence of *analytic* words, the overall average for all local authorities being 97.8. All have a stable trend, averaging 96-98 over the years analysed, the exception being Roscommon, which has a decreased presence of *analytic* words from 2015 to 2021, followed by an increase from 2022, making it more in line with other local governments. A new CE was appointed to Roscommon in 2015, remaining in office until 2021, corresponding with the lower *analytic* words. This suggests that this particular CE is a variable affecting the textual characteristics of the budget report.

The LIWC-22 variable *clout* captures language associated with leadership and status – see Table 2. It has been used to assess for example the language used by politicians (Underberg et al., 2020). Here, it is assumed that the position of CE of a local government holds some status and thus we would expect some evidence of *clout* words. The overall average value for *clout* is 49.57 (out of 100) across all local governments. As can be seen in Figure 3, the *clout* values vary from about 32 to 82. The lowest average is Dublin City (36.79), with Roscommon being the highest (67.77). The averages for *clout* are higher generally in the rural local governments in the sample. A more detailed qualitative study would be needed to tease out why this is so, but a potential reason may be less complex budgeting procedures in rural governments conferring more power on their CE. *Tone net* is the sum of two variables from LIWC-22, namely *tone_pos* and *tone_neg*. These two variables capture words conveying a positive and negative sentiment respectively and are measured as a percentage of total words. As shown in Figure 4, the *tone net* results range from approximately 0.5 to 3.6% of total words. The overall average is 1.82%. While not shown in Table 3, *tone_pos* is more prevalent than *tone_neg*, averaging overall at 2.07% and 0.25% respectively. Again, a difference is apparent between rural and urban local governments, with the rural values being generally higher than urban. Overall, though, the values for *tone net* suggest a quite neutral use of language in the CE's budget report.

The *work* and *money* variables from LIWC-22 are included in the analysis respectively, as a local government budget is in essence a plan of work to be done expressed in monetary values. Thus, it may be expected that any commentary on a budget would include *work* and *money* words. Both variables are represented as a percentage of total words and the results can be seen visually in Figures 5 and 6. For the *work* variable, the overall average is 6.29% of total words, ranging from 5.6% in Dublin City to 7.48% in Monaghan. For the *money* variable, the results fall within a comparable range. The overall average is 5.37% of total words, with values ranging from 3.72% in Monaghan to 6.82% in Dublin. Combined, the *work* and *money* variables account for nearly 12% of the total words in the documents on average. While no prior studies have specifically analysed the *work* or *money* variables in a local government context, Boyd et al. (2022) report that the average value for the *work* variable in *The New York Times* texts is 3.39%, while in conversational settings it averages 2.47%. This comparison suggests that the higher average value of 6.29% observed here reflects the substantial effort involved in preparing these budgets. Prior research on text in loan applications has shown a correlation between the use of *money* words and success of the loan application (Larrimore et al., 2011). Following a similar logic, for the CE's budget report it is possible that the use of *money* words – captured in detailed explanations for expenditure – ensures the budget is approved by locally elected representatives.

The final two LIWC-22 variables analysed are *focus present* and *focus future*, and the results can be seen in Figures 7 and 8. Textual characteristics such as words related to the past, present and future have been studied previously in the accounting literature in relation, for example, to impression management. For example, Moreno et al. (2019, p.1717) noted "that a decrease in profitability can result in an increase in future references because a focus on future opportunities can divert attention from past poor performance", which is in line with earlier research (e.g. Poole, 2016). Here, the LIWC-22 variable *focus past* was not used, as it is expected that texts related to budgets would typically reflect present and future focused language, with an expectation that future focus would be more prevalent. Overall, the average for *focus present* 2.89% of total words, with the average for *focus future* being 2.00%. As can be seen in Figure 7, the prevalence of *focus present* is quite varied across the local governments and across time; Figure 8 portrays a more stable pattern for the *focus future* variable across both local governments and time. Only Roscommon shows a higher prevalence of the *focus future* variable over *focus present*. On the other hand, Fingal has a consistently wider gap than other local governments, with *focus present* being typically 2-2.5% greater than *focus future*, i.e. approximately twice as many words focusing on the present. More detailed research would be necessary to ascertain why this is so. As per Table 2, the *focus future* and *focus present* variables were included to determine if too much focus was given to commentary on the present in an effort to distract from future plans. While the prevalence of *focus present* is higher on average, the difference to *focus future* is not substantial and thus it is suggested that, on average, distraction from the future is not a tactic being employed, although Fingal could be showing some initial signs of obfuscating its budgeting efforts (Courtis, 2004).

Table 3. LIWC-22 results for all variables used

L. Gov, Year	Word count	Analytic	Clout	Tone net	Work	Money	Focus present	Focus future
Cork, 2012	3665	98.29	45.86	1.36	7.53	4.45	3.25	1.91
Cork, 2013	3841	98.29	40.53	1.15	6.43	5.10	3.85	2.27
Cork, 2014	3547	98.80	46.05	1.78	6.37	4.85	3.64	2.20
Cork, 2015	3005	98.32	45.76	1.93	6.46	5.12	3.36	2.40
Cork, 2016	3240	98.25	43.88	1.69	5.99	4.88	3.27	2.16
Cork, 2017	3574	98.10	46.68	1.79	6.32	5.12	3.44	2.21
Cork, 2018	3528	97.91	44.93	1.93	6.15	5.27	3.43	2.41
Cork, 2019	3852	97.89	44.52	1.74	5.69	5.09	3.61	2.49
Cork, 2020	4333	98.23	43.32	1.78	5.24	4.59	3.44	2.31
Cork, 2021	2806	98.13	49.39	1.50	5.42	4.81	2.89	1.82
Cork, 2022	2839	98.07	49.70	1.59	5.49	4.37	2.64	2.04
Cork, 2023	2958	97.55	48.70	1.52	5.38	5.14	2.97	2.40
Dublin, 2012	3071	98.50	42.74	1.95	6.71	5.08	2.77	1.76
Dublin, 2013	3927	98.38	45.48	1.27	6.37	4.94	2.55	1.73
Dublin, 2014	2457	98.41	38.17	1.06	5.21	6.55	2.48	1.79
Dublin, 2015	2646	98.22	35.31	0.87	5.40	7.56	2.49	1.70
Dublin, 2016	4515	98.48	35.25	1.07	5.29	7.15	2.75	1.44
Dublin, 2017	4245	97.42	32.64	0.73	5.54	7.40	2.90	1.25
Dublin, 2018	4815	97.52	33.36	1.19	5.46	7.58	2.60	1.20
Dublin, 2019	3342	97.31	31.36	0.72	5.15	8.41	3.11	0.93
Dublin, 2020	2585	97.10	35.63	1.36	5.15	8.01	3.83	1.59
Dublin, 2021	1685	97.44	35.31	0.77	6.35	7.30	3.80	1.72
Dublin, 2022	2796	96.86	40.71	1.40	4.90	5.76	3.33	1.61
Dublin, 2023	3001	98.22	35.48	1.13	5.63	6.10	2.97	1.40
Fingal, 2012	2204	97.56	48.69	1.36	6.44	5.54	3.31	1.32
Fingal, 2013	2427	98.72	49.87	2.06	6.43	6.10	2.14	1.40
Fingal, 2014	1941	98.80	49.87	2.52	8.45	5.72	3.14	1.80
Fingal, 2015	1508	98.96	66.91	3.12	7.29	5.64	2.52	1.06
Fingal, 2016	2264	98.60	73.23	2.74	7.33	5.65	3.75	1.15
Fingal, 2017	2811	99.00	45.94	1.85	7.40	7.19	3.38	1.17
Fingal, 2018	2521	99.00	45.00	1.35	7.85	8.01	3.77	1.23
Fingal, 2019	2483	99.00	45.07	1.21	7.25	7.77	3.46	1.09
Fingal, 2020	1191	99.00	56.59	2.44	6.13	7.14	2.77	0.76
Fingal, 2021	1334	99.00	52.58	1.50	5.55	5.70	2.70	1.27
Fingal, 2022	1735	99.00	59.26	2.76	6.17	4.84	3.52	1.04
Fingal, 2023	1735	99.00	59.26	2.76	6.17	4.84	3.52	1.04

L. Gov, Year	Word count	Analytic	Clout	Tone net	Work	Money	Focus present	Focus future
Galway, 2012	1936	97.19	53.63	0.93	5.79	8.01	3.82	2.12
Galway, 2013	2029	97.73	59.42	1.18	5.47	6.75	3.84	2.56
Galway, 2014	4342	98.02	47.15	2.46	6.43	4.28	2.90	2.23
Galway, 2015	7243	98.64	38.94	2.31	6.27	4.27	3.23	2.39
Galway, 2016	6924	97.73	30.88	1.40	4.75	4.61	3.45	2.79
Galway, 2017	6275	98.19	35.06	1.94	5.21	4.27	3.35	2.98
Galway, 2018	2521	98.19	52.13	1.63	5.47	6.74	2.22	1.31
Galway, 2019	2345	98.08	49.70	1.71	6.27	6.91	2.64	1.71
Galway, 2020	2340	97.39	42.82	1.79	5.64	7.39	2.61	2.01
Galway, 2021	6753	97.98	34.91	1.54	5.83	5.51	3.35	2.06
Galway, 2022	13088	98.00	37.30	1.36	6.15	4.47	3.18	2.38
Galway, 2023	8084	98.67	38.91	1.64	5.91	4.68	3.34	2.40
Limerick, 2012	4667	97.97	38.07	0.95	4.82	6.99	2.64	1.74
Limerick, 2013	5609	97.60	38.51	0.90	5.17	7.35	2.57	1.93
Limerick, 2014	4509	97.39	42.67	1.27	6.03	6.23	2.48	2.11
Limerick, 2015	3465	98.23	44.85	2.23	5.86	5.14	2.66	1.44
Limerick, 2016	4587	98.69	38.67	1.81	6.45	6.19	2.51	1.22
Limerick, 2017	4721	98.65	39.69	1.63	6.44	6.46	2.63	1.48
Limerick, 2018	5971	98.25	44.12	2.11	6.95	5.19	3.00	1.79
Limerick, 2019	6493	98.39	48.57	1.94	6.15	5.16	2.51	1.99
Limerick, 2020	6915	98.37	48.30	1.65	6.13	5.47	2.59	2.14
Limerick, 2021	7341	98.51	47.98	1.50	5.95	5.78	2.44	1.48
Limerick, 2022	7171	98.47	47.33	1.50	5.88	5.79	2.38	1.55
Limerick, 2023	7188	98.45	41.22	1.55	5.55	6.23	2.71	1.75
Monaghan, 2012	1128	98.28	35.00	0.44	6.38	6.38	4.08	1.86
Monaghan, 2013	616	99.00	48.74	2.28	8.77	6.01	1.46	1.62
Monaghan, 2014	1114	98.99	58.76	2.06	9.07	3.77	2.33	3.59
Monaghan, 2015	1016	95.97	65.03	3.35	4.72	3.94	2.26	2.66
Monaghan, 2016	550	96.85	76.03	3.09	6.18	4.55	2.73	1.82
Monaghan, 2017	1232	98.19	53.14	3.09	7.55	4.55	2.03	2.35
Monaghan, 2018	1534	98.19	61.74	2.41	7.89	2.93	2.28	2.93
Monaghan, 2019	1566	98.50	60.57	3.13	7.34	2.49	2.17	2.68
Monaghan, 2020	2229	98.30	58.23	2.56	7.67	2.06	2.33	2.65
Monaghan, 2021	1565	98.34	59.07	2.62	8.88	2.75	2.68	1.73
Monaghan, 2022	1294	99.00	52.97	2.55	8.50	2.63	2.24	1.85
Monaghan, 2023	1355	98.13	59.83	2.88	6.79	2.58	2.88	2.95
Roscommon, 2012	2890	96.67	60.04	1.35	7.27	6.06	3.11	2.08
Roscommon, 2013	3397	97.42	58.46	1.79	6.68	5.30	2.56	1.68
Roscommon, 2014	3920	98.02	56.50	2.35	5.97	4.74	3.09	2.32
Roscommon, 2015	3651	97.25	56.73	2.36	8.82	5.01	2.99	2.33
Roscommon, 2016	724	95.08	79.09	3.45	6.22	3.31	2.21	3.87
Roscommon, 2017	1109	94.93	62.51	2.44	3.88	3.16	3.16	2.71
Roscommon, 2018	1112	89.27	66.00	2.25	4.68	3.69	3.87	3.87
Roscommon, 2019	697	92.96	83.65	2.73	4.45	3.59	2.87	5.02
Roscommon, 2020	1007	88.82	66.87	2.58	6.06	1.99	3.28	3.38
Roscommon, 2021	1210	90.83	79.01	2.73	5.62	3.47	2.48	3.97

L. Gov, Year	Word count	Analytic	Clout	Tone net	Work	Money	Focus present	Focus future
Roscommon, 2022	1776	96.79	69.56	3.66	6.14	2.53	2.42	3.10
Roscommon, 2023	1064	97.30	74.82	3.20	7.24	2.82	3.01	2.54
Tipperary, 2015	2166	98.95	42.77	1.25	7.80	6.14	3.14	1.43
Tipperary, 2016	3022	98.64	57.04	1.53	6.35	6.02	2.32	1.22
Tipperary, 2017	3803	98.47	55.42	1.21	6.00	5.60	1.79	1.24
Tipperary, 2018	3256	98.63	52.34	1.20	5.87	5.31	2.06	1.41
Tipperary, 2019	2278	99.00	38.53	1.06	7.20	6.98	2.50	1.71
Tipperary, 2020	3247	99.00	37.40	1.08	6.22	6.34	2.46	2.00
Tipperary, 2021	3813	98.68	48.16	0.76	7.00	5.95	2.70	1.18
Tipperary, 2022	3826	98.34	45.17	1.00	7.00	6.51	2.56	1.99
Tipperary, 2023	4469	98.40	46.54	1.18	6.35	5.44	2.19	1.59

Figure 1. *Word count* of CE's budget report

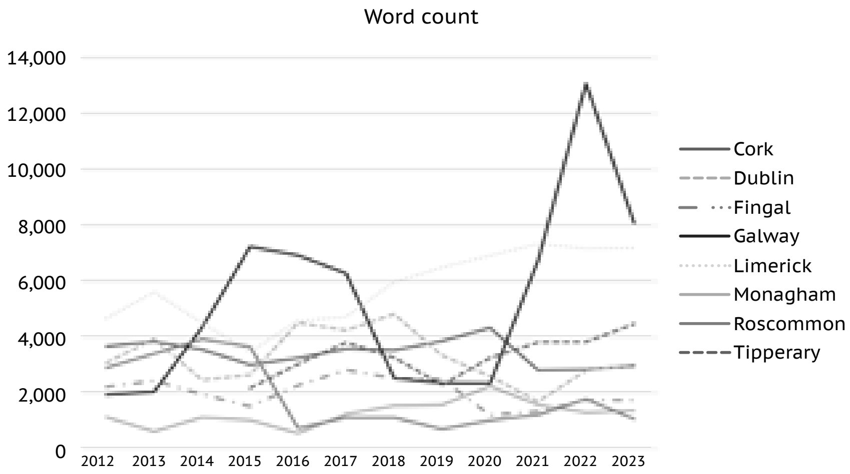


Figure 2. *Analytic* variable represented in CE's budget report

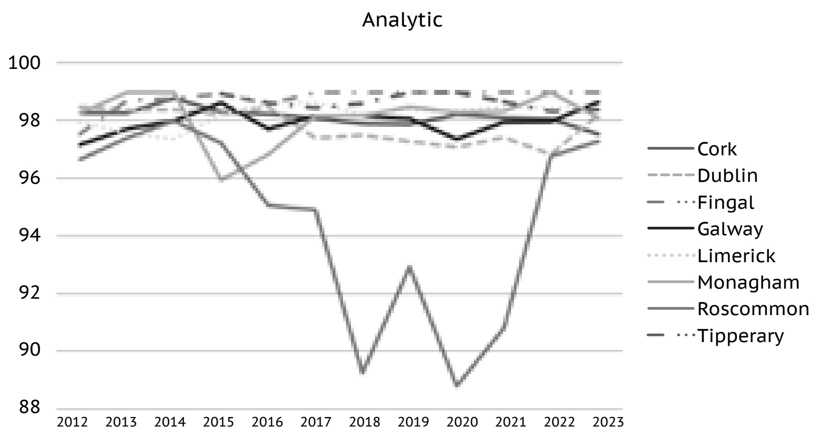


Figure 3. *Clout* variable represented in CE's budget report

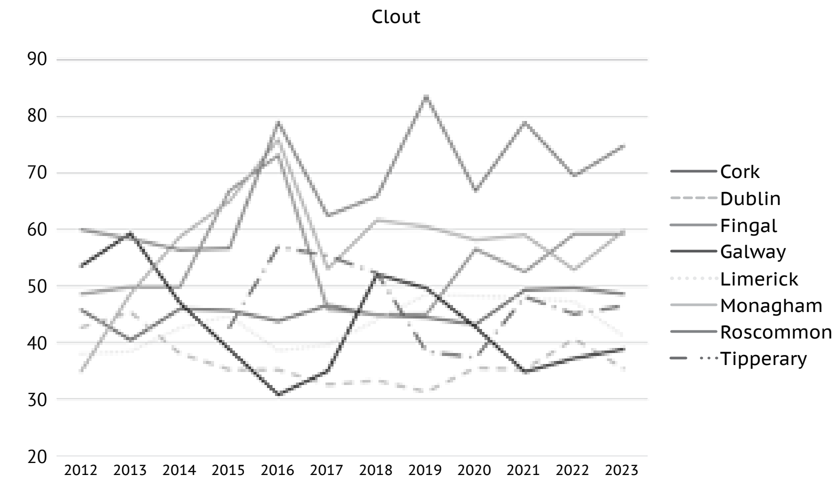


Figure 4. *Tone net* variable represented in CE's budget report

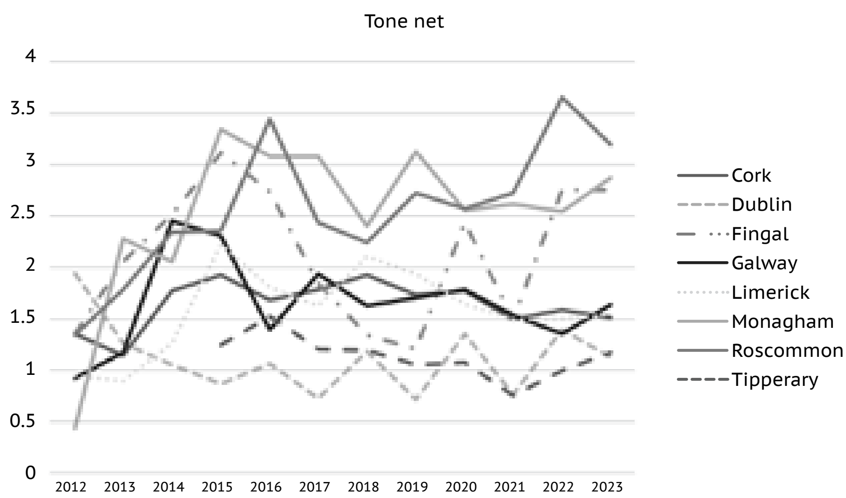


Figure 5. *Work* variable represented in CE's budget report

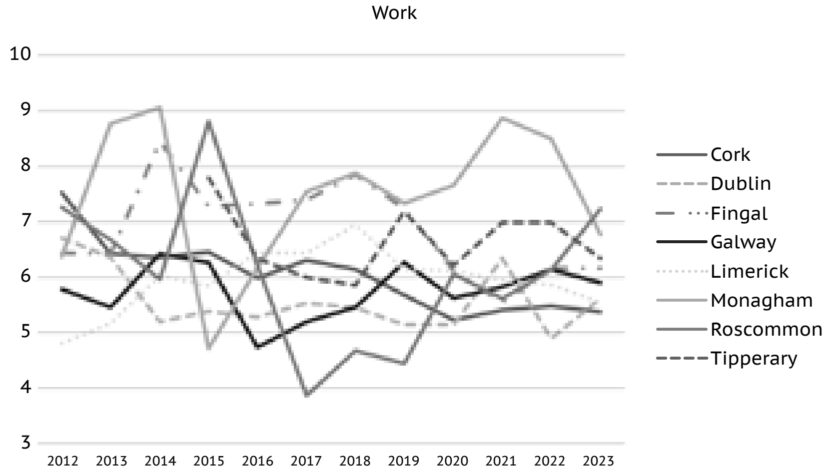


Figure 6. *Money* variable represented in CE's budget report

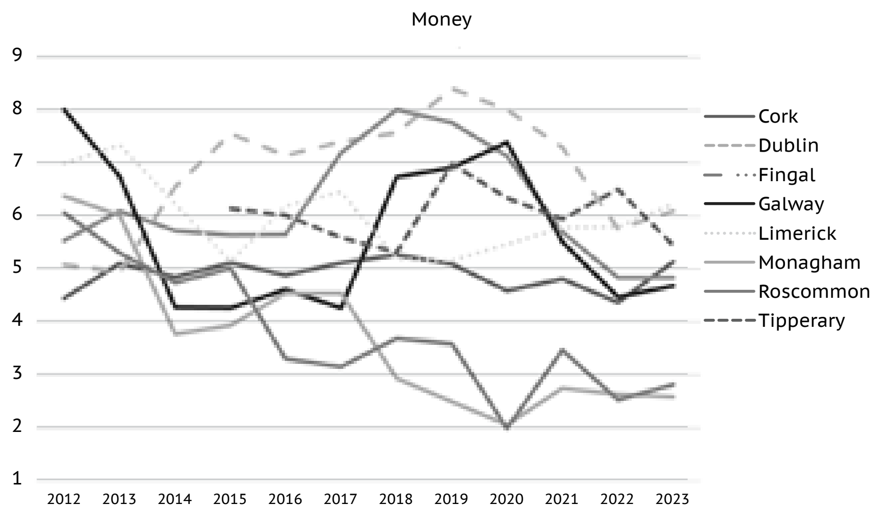


Figure 7. *Focus present* variable represented in CE's budget report

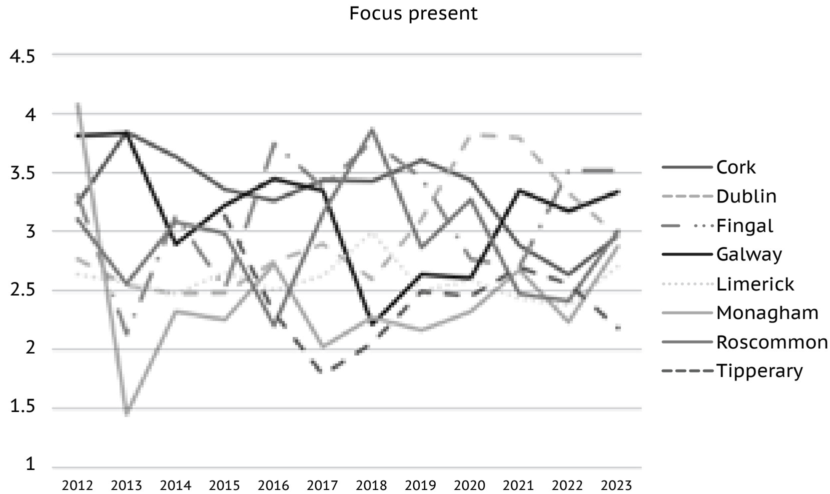
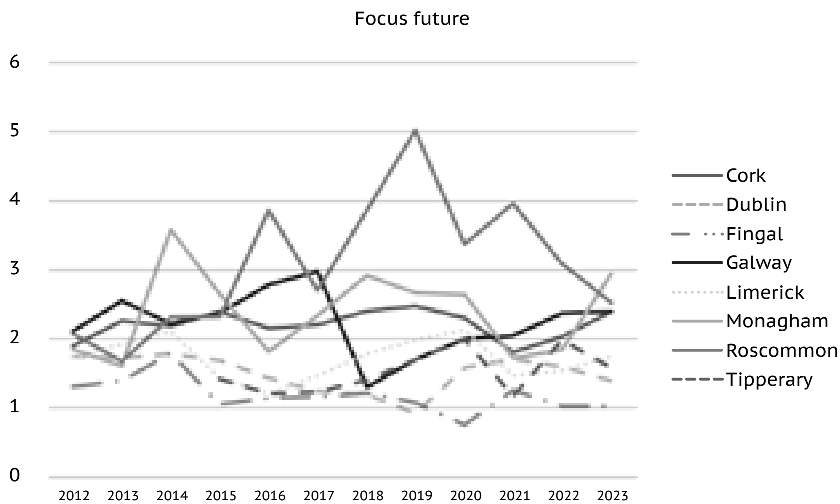


Figure 8. *Focus future* variable represented in CE's budget report



Earlier, some apparent pattern differences between urban and rural local governments were noted. This prompted us to subject the LIWC-22 data to some statistical tests. As mentioned in Section 3 and see also Table 1, our analysis comprises eight local governments with differing demographical profiles. We also have less CE budget reports for Tipperary compared to the other local governments. Thus, we tested the data for normality and homoscedasticity. We grouped the local governments into two groups representing urban and rural. The grouping of urban versus rural followed Table 2, with Fingal regarded as rural. The results of a Shapiro-Wilk test on the eight LIWC-22 variables reveal that *clout* and *work* meet the requirements for normality and homoscedasticity, but the other six do not (at 5% significance). We thus regard the two groups (urban and rural) as non-parametric samples and performed a Mann Whitney test, the results of which can be seen in Table 4. The results are significant at 5% for all variables except *clout* and *future focus*, implying the two groups are different, i.e. there is a difference between the textual characteristics in the CE budget reports of urban and rural governments. A significant urban-rural divide has been noted in Ireland for many years (see e.g., Flynn, 2024), and according to the 2022 Census of Population in Ireland, approximately 3.26 million[ii] people of a total population of 5.08 million (i.e. 64%) live in an urban setting. While further research would be required to tease out this observation, there would appear to be some evidence of an urban/rural divide in the textual characteristics of the analysed CE budget reports.

Table 4. Results of Mann-Whitney test

Independent-Samples Mann-Whitney U Test Summary	Word count	Analytic	Clout	Tone_pos	Tone_neg	Work	Money	Focus present	Focus future
Total N	93	93	93	93	93	93	93	93	93
Mann-Whitney U	272.5	1303.5	1899	1568	715.5	1668.5	744.5	780	1054.5
Wilcoxon W	1307.5	2338.5	2934	2603	1750.5	2703.5	1779.5	1815	2089.5
Test Statistic	272.5	1303.5	1899	1568	715.5	1668.5	744.5	780	1054.5
Standard Error	130.076	129.958	130.075	130.067	130.011	130.066	130.072	130.067	130.069
Standardized Test Statistic	-6.208	1.72	6.296	3.752	-2.804	4.525	-2.579	-2.307	-0.196
Asymptotic Sig. (2-sided test)	<.001	0.085	<.001	<.001	0.005	<.001	0.01	0.021	0.845

Note: *Tone_pos* and *Tone_neg* are significant at 1%. We also tested *Tone Net*, which gave the same results.

4.2. Insights from customised coding

Insights from text obtained from LIWC-22 (or any other off-the-shelf software) are limited in that the software is not customisable. As mentioned in the methods section, such limitations can be overcome by utilising customised code written in Python (or other coding languages). In this study, we used customised code to analyse the readability of the CE's budget report via the Fog and Box indices, and to search for some specific words. The results of these two tasks are now outlined.

The results of the two readability indices are shown in Table 5. A readability index of 17 for the Gunning Fog index equates to the reading level of a college graduate. As can be seen in Table 5, the results from all local governments for all year's show an average Gunning Fog index above 17. The overall average Gunning Fog index across the 93 texts analysed is 20.8. These index values suggest the CE's budget reports are complex. As reported earlier, the average word count of the documents analysed here was 3,275 words and it has been noted that a higher word count is associated with complexity and reduced readability (Loughran and McDonald, 2016). Roundy et al. (2023) reported a Fog index of 27.59 in their study of annual reports – i.e. less readable than the documents analysed here – and their average word count was 29,316. Roundy et al.'s (2023) study linked readability to the usefulness of annual reports of local government. They suggested that for local government annual reports to be a useful communication tool, they should be understandable by general audiences. Their findings on readability suggest the annual reports are complex and are less useful to a general audience. The findings here seem to support their assertion, albeit in a different document and a different local government context.

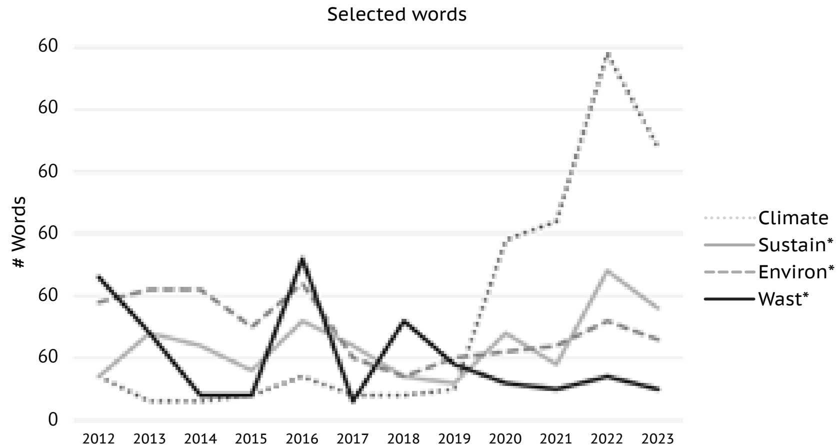
Table 5. Gunning Fog and BOG readability indices

Year	Cork City	Dublin City	Galway City	Limerick City & County	Fingal	Monaghan	Roscommon	Tipperary
BOG Index								
2012	30.82	23.02	27.72	26.69	27.09	22.04	28.21	
2013	29.14	25.59	34.01	28.76	35.99	22.08	30.04	
2014	30.38	26.08	26.54	24.09	28.92	26.38	33.94	
2015	29.18	29.75	27.65	28.18	35.52	31.48	34.79	28.62
2016	28.33	27.30	27.46	31.17	30.57	33.41	43.16	29.58
2017	28.17	25.22	27.70	34.96	28.47	38.95	38.07	31.23
2018	26.04	26.62	64.93	34.89	24.77	33.39	37.84	32.88
2019	25.15	24.10	58.17	35.48	24.87	36.01	46.97	27.91
2020	26.31	23.87	49.01	35.05	26.64	33.87	37.71	32.08
2021	25.43	26.22	37.30	35.50	27.25	27.77	38.99	33.92
2022	24.97	26.72	35.94	36.67	28.33	30.49	30.52	27.27
2023	26.57	24.32	31.79	36.08	28.33	30.29	31.54	32.73
Avg.	**27.54**	**25.73**	**37.35**	**32.29**	**28.89**	**30.51**	**35.98**	**30.69**
Gunning Fog Index								
2012	20.89	16.80	18.76	18.59	19.06	15.82	20.31	
2013	19.94	17.71	21.67	19.45	24.23	16.59	21.18	
2014	20.35	17.77	18.97	17.49	20.09	19.03	22.97	
2015	19.92	19.86	19.18	19.06	22.57	20.62	23.71	20.48
2016	19.37	18.42	18.47	20.67	21.08	21.67	26.47	20.71
2017	19.16	17.65	18.67	22.56	19.98	24.80	23.78	21.62
2018	18.04	18.18	36.02	22.77	18.13	22.16	23.42	22.22
2019	17.81	16.93	33.06	22.66	18.15	23.30	28.11	19.74
2020	17.52	16.56	28.94	22.52	19.60	22.62	23.91	21.54
2021	17.14	17.25	23.18	22.26	19.61	19.51	24.33	22.65
2022	17.15	17.26	22.69	22.89	19.40	20.73	21.08	19.51
2023	17.69	16.71	21.74	22.49	19.40	20.66	21.67	21.52
Avg.	**18.75**	**17.59**	**23.45**	**21.12**	**20.11**	**20.63**	**23.41**	**21.11**

It was noted earlier that the Bog Index is designed for business specific text and is potentially a better reflection of the readability of such documents (Bonsall et al., 2017). It can be seen in Table 5 that the average Bog Index across all years falls within the good readability range (i.e. 21-40). The two readability indices thus contradict each other and the choice of readability index to use is likely best determined by the objectives/context of a particular study. As can be seen in Table 5, both indices return quite stable values. The one exception is Galway City, which from 2018 to 2020 shows poorer readability according to both indices. An inspection of the CE's budget reports from 2017 to 2022 does not reveal a change in CE and can thus be ruled out as an influencing factor. The format of the documents did however change in 2018, with a greater use of shorter bullet point sentences with more complex words therein. This in turn yielded a poorer Bog Index, albeit still within the average readability range.

The second task using custom python code was to search the CE's budget reports for the word stems from the words "recycle, "carbon", "circular", "climate", "emissions", "renewable", "sustainable" and "waste". As mentioned in the methods section, the words are general in nature and the intention is to illustrate the use of customised content analysis methods. While the code found all words in the CE's budget reports, some showed quite low prevalence. For example, emiss* only revealed 15 matches, with recycl* revealing 17 matches. In both these examples, the presence of the words is in the most recent years. The top four words from the above list found were climat*, sustain*, environ* and wast*. The trends of the prevalence of these four words across all local governments analysed can be seen in Figure 9. As can be seen, the stem climat* shows a greater prevalence from 2020 onwards, with the other three-word stems being within a stable range. A closer inspection of the CE's budget report reveals a greater degree of commentary following the Irish central government's Climate Change Action Plan of 2019 – the 2020 local government budgets were the first to take this plan into consideration. It is worth noting that words such as "climate" are more prevalent in the full budget document – here we analyse only the CE's report within the budget. While this study does not directly engage with sustainability reporting literature, the increased prevalence of words such as "climate" in the CE's budget reports following the introduction of formal central government plans mandating consideration of climate change aligns with findings in that literature (e.g., Christensen et al., 2021).

Figure 9. Trends of *Selected words* from CE's budget report



5. Concluding comments

This study highlights the potential of computerised content analysis methods in the domain of local government research, addressing a significant gap in the literature. By focusing on the CE's reports within Irish local government budget documents, this research demonstrates the value of both off-the-shelf tools like LIWC-22 and custom Python coding for extracting meaningful insights from textual data. These methods offer a powerful complement to traditional approaches, enabling the analysis of large datasets with greater efficiency, consistency, and depth.

The findings illustrate that computerised content analysis provides new avenues for understanding the textual characteristics of local government documents, such as readability, sentiment and thematic focus. For instance, this study identified key differences in textual complexity and thematic emphasis across urban and rural governments, as well as temporal trends reflecting broader policy influences, such as climate change action plans. Such insights not only have potential to enhance our theoretical understanding but may also have practical implications for improving the clarity, transparency, and understandability of local government communications.

Despite the contributions here and the potential of computerised content analysis, this research recognises certain limitations. The scope of analysis here was confined to budget documents from a subset of Irish local governments, and the tools used, while advanced, are not exhaustive. Future research could expand the dataset to include a broader range of documents and contexts, or explore other computerised content analysis tools and techniques, such as machine learning models for semantic analyses. Furthermore, integrating stakeholder perspectives could provide additional insights into the practical applications and reception of such methods.

In conclusion, this study illuminates the importance of adopting innovative methodologies to analyse the rich and yet underutilised textual data produced by local governments. By bridging a methodological gap and offering empirical evidence, it sets the stage for further exploration of computerised content analysis as a cornerstone of public service research, ultimately fostering greater accountability, transparency, and informed decision-making within the public sector.

Endnotes

[i] One author is experienced in Visual Basic and Unix scripting. These skills allowed the author to edit, test and perfect code generated by Microsoft Co-Pilot.

[ii] See http://data.cso.ie , Census 2022, table FY107.

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