Journal of Economic Criminology 11 (2026) 100207

Contents lists available at ScienceDirect

Journal of Economic Criminology

journal homepage: www.journals.elsevier.com/journal-of-economic-criminology

# Accounting scripts and the politics of compliance: Understanding accountants' roles in anti-money laundering through sentiment and script theory

Mark E. Lokanan [1]

*Faculty of Management, Royal Roads University, 2005 Sooke Road, Victoria, BC V9B 5Y2, Canada*

ARTICLE INFO

*Keywords:*
Money laundering
Accountants
Script theory
Deep learning

ABSTRACT

This study explores the role of accountants in anti-money laundering (AML) compliance within Canada's non-banking financial institutions, specifically focusing on the real estate, luxury vehicles, and gaming sectors. By utilizing a unique combination of machine learning (ML) and deep learning (DL) algorithms, along with natural language processing techniques, the research conducts sentiment analysis on the testimonies of accountants who appeared at the Cullen Commission inquiry. Supported by semi-structured interviews with key gatekeepers, this study provides a comprehensive understanding of accountants' perspectives and experiences in AML compliance. The sentiment analysis, utilizing both ML and DL models, reveals a predominance of positive sentiments among the testimonies, indicating overall satisfaction with regulatory frameworks and participation in AML initiatives. Neutral sentiments emphasize the provision of factual descriptions of procedures and regulations, while negative sentiments highlight concerns regarding the effectiveness of AML measures. Applying script theory as a cognitive framework, the study categorizes accountants' cognitive processing into three stages: preexisting schemata, assimilation, and accommodation. These stages illustrate the progression of accountants' perspectives and strategies in response to AML compliance challenges, ranging from reliance on previous experiences and beliefs to the integration of new information and adjustment to regulatory changes. The findings offer fresh insights into the field of accounting scholarship, particularly in critical accounting research. The utilization of advanced DL methods in sentiment analysis represents a methodological innovation, allowing for a deeper comprehension of accountants' roles in AML compliance.

## 1. Introduction

A series of investigations by *The Globe and Mail* in 2018 first documented the depth and complexity of money laundering in British Columbia's real estate and casino sectors (Tomlinson, 2018; Tomlinson and Xiao, 2018). These reports showed how private lenders with criminal connections financed property purchases and gambling debts at predatory interest rates. They raised concerns about the complicity or negligence of professionals—particularly those in finance and accounting—who are expected to act as gatekeepers against financial crimes.

Since then, the problem has become clearer as a systemic and persistent issue. A recent report by the Canadian Broadcasting Corporation (CBC) indicates that money laundering continues to flourish in the province. In late 2024, a British Columbia man was charged in connection with a $47 million laundering scheme linked to the illegal cannabis trade, which demonstrates the resilience and reach of these criminal networks (Canadian Broadcasting Corporation, 2025). Legal experts and commentators argue that government inaction may reflect the economic benefits derived from illicit funds circulating through the real estate market and financial system (Todd, 2024). These developments show that money laundering in British Columbia is not a historical anomaly but an ongoing challenge. Despite public inquiries, policy reforms, and heightened regulatory scrutiny, illicit financial activity remains deeply embedded in the province's economy. The persistence of these practices indicates the need for continued vigilance and structural reform (German, 2019; Maloney et al., 2019).

In response to these developments, the Government of British Columbia established the Cullen Commission in 2019. Headed by British Columbia Supreme Court Justice Austin Cullen, the Commission

*E-mail address:* Mark.Lokanan@royalroads.ca.
[1] royalroads.ca

https://doi.org/10.1016/j.jeconc.2026.100207
Received 6 November 2025; Received in revised form 20 January 2026; Accepted 24 January 2026
Available online 3 February 2026

examined the scope of money laundering in the province, assessed the response of regulatory agencies and law enforcement, and evaluated the impact on the economy and society. A central focus was the role of professionals—accountants, lawyers, and notaries—in laundering activities in real estate, luxury car sales, and casinos. The Commission's final report, released in June 2022, included an 85-page section titled *"Accountants,"* which analyzes the accounting sector and its anti-money laundering (AML) responsibilities under the *Proceeds of Crime* (Money Laundering) and *Terrorist Financing Act* (PCMLTFA) (Cullen, 2022b).

The paper examines sworn testimonies provided by accountants to the Cullen Commission to explain why AML compliance functions unevenly within non-banking financial institutions (NBFIs) in British Columbia, including real estate, luxury vehicles, and gaming sectors. Accountants occupy a pivotal gatekeeping position in these sectors, and their interpretations of responsibility, authority, and constraint shape how AML rules are enacted in practice. Machine and deep learning algorithms, combined with natural language processing (NLP) techniques, analyze sentiment patterns in testimony to identify how accountants evaluate, justify, and delimit their AML obligations. Semi-structured interviews with accountants and other AML stakeholders provide contextual context for these evaluative narratives. Guided by script theory (Schank and Abelson, 1975, 2013), the analysis examines how professional scripts reveal institutional, regulatory, and enforcement conditions that help explain when AML compliance succeeds and when it falters. The central research question asks: How do accountants' professional scripts and evaluative narratives illuminate the structural conditions under which AML enforcement functions effectively or breaks down in Canada's NBFI sectors? Addressing this question positions accountants' perspectives as essential to understanding AML performance, with implications for regulators, policymakers, and scholars of economic crime.

The study makes three interrelated contributions to the interdisciplinary literature on economic crime and AML compliance. First, the analysis advances theoretical understanding of AML enforcement by applying script theory to examine how accountants, as institutional intermediaries, interpret and enact their gatekeeping role within non-banking financial institutions. While script theory has been widely applied in cognitive psychology and criminology, its use in accounting research—particularly in relation to money laundering—remains limited. Prior accounting studies have applied scripts to auditing contexts and judgment formation (Choo, 1989, 1996; van der Steen, 2009; Löhlein and Huber, 2024). Extending this work, the present study demonstrates how professional scripts shape accountants' evaluative narratives, revealing structural and regulatory constraints that affect the functioning of AML enforcement beyond the accounting profession itself. In doing so, the study responds to calls for greater engagement with social and psychological theory in accounting and governance research (Unerman and Chapman, 2014), while situating accountants within broader economic crime control systems.

Second, the study contributes empirically to the AML and economic crime scholarship by providing rare, systematic evidence drawn from sworn testimonies and practitioner interviews. By analyzing how accountants publicly justify, limit, or critique their AML responsibilities, the paper shows that accountants are not peripheral technical actors but are deeply implicated in the effectiveness of AML regimes. These findings are of direct relevance to regulators, policymakers, law enforcement agencies, and scholars concerned with why AML systems may underperform despite formal compliance frameworks.

Third, the study contributes methodologically by demonstrating how machine and deep learning–based sentiment analysis helps explain institutional features of AML enforcement rather than promote methodological techniques. Unlike conventional qualitative coding or doctrinal analysis, the sentiment-based approach enables systematic identification of evaluative patterns across sworn testimony, revealing how accountants repeatedly frame responsibility, authority, and constraint under regulatory scrutiny. Advanced models such as CNN, LSTM, and BERT detect consistent linguistic signals associated with structural limitations and enforcement gaps that may remain implicit or episodic in interview-based analysis (Davidescu et al., 2023; Han et al., 2020; Kute et al., 2021). Embedded within a script-theoretic framework, these methods help explain how institutional conditions shape AML performance, rather than merely classifying text or promoting methodological novelty.

The rest of this paper is structured in the following format: Section 2 reviews the accounting literature pertinent to AML compliance and regulation. In Section 3, script theory is outlined, detailing the three stages of schemas used in processing event-specific information, complemented by a discussion on sentiment analysis for textual data analysis. Section 4 elaborates on the methodology and experimental settings, encompassing both interviews and sentiment analysis techniques. Section 5 presents a dual analysis: a quantitative assessment of accountants' testimonies at the Cullen Commission using advanced machine and deep learning algorithms, and qualitative insights derived from semi-structured interviews with professionals involved in AML compliance. The findings are then discussed in Section 6, focusing on accountants' roles in AML compliance within the framework of script theory. The paper concludes in Section 7, summarizing the study's key findings, acknowledging its limitations, and proposing directions for future research on AML compliance in accounting.

## 2. Literature review

### *2.1. Anti-money laundering issues in the accounting literature*

The critical development regarding the importance of accounting in AML compliance has not received the scholarly attention it deserves. Despite a growing body of literature on the role of accountants in detecting and preventing fraud in general (Gabbioneta et al., 2013; M. Lokanan, 2018; Morales et al., 2014; Power, 2013; Sathye, 2024), the scholarship remains limited on the importance and application of accounting knowledge in the construction and detection of money laundering operations (Amara et al., 2020; Bolgorian and Mayeli, 2020; Compin, 2008; Mitchell et al., 1998; Norton, 2018; Ravenda et al., 2019; Sikka and Willmott, 1998). Given that regulatory agencies recognize the accounting profession as a key gatekeeper in detecting money laundering and terrorist financing (ML/TF) activities (Lawrence et al., 2010; Martini, 2017), the limited volume of accounting-specific scholarship in this area indicates a disconnect between the profession's formally assigned regulatory role and the extent to which its AML responsibilities have been systematically examined in academic research.

The literature assembled to date focuses on accountants and their compliance duties in detecting money laundering transactions (Amara et al., 2020; Compin, 2008; Mitchell et al., 1998; Norton, 2018; Ravenda et al., 2019). A second strand of literature examines whether accountants and accounting firms are seen as gatekeepers who prevent and detect money laundering activities or whether they are complicit in enabling the illicit movement of funds through the creation of shell companies and fictitious billing networks (Bolgorian and Mayeli, 2020; Habib et al., 2020; Lawrence et al., 2010; Mitchell et al., 1998; Sikka and Willmott, 1998). The Financial Action Task Force questions the ease with which anonymous companies or trusts can acquire property and launder money and the role of gatekeepers such as real estate agents, lawyers, and accountants, who may act as facilitators in transactions that enable money laundering schemes (de Koker et al., 2025, pp. 5–6; Martini, 2017, p. 5).

To the extent that the issue of money laundering operations has been taken up as an object of analysis in the accounting literature (Compin, 2008; Lawrence et al., 2010; Norton, 2018; Sathye, 2024), the accounts have focused, more generally, on the role of the regulatory apparatus in shielding accountancy firms from scrutiny (Mitchell et al., 1998); the importance of accounting knowledge in the construction of money laundering operations (Amara et al., 2020; Compin, 2008); the deployment of regulation that compromises the auditor–client relationship (Löhlein and Huber, 2024; Norton, 2018); and auditor-fee considerations and client risks (Habib et al., 2020). Moreover, scholarship in this area typically adopts as its focal point the role of accountants and institutions in managing fraud, including the reality and reconstruction of human frailties (Davis and Pesch, 2013; Lehman and Okcabol, 2005; Morales et al., 2014), and, in the rare instances when serious cases are in the limelight, the tendency to examine the role of accounting in understanding crime as a social phenomenon and as a social construction (Lehman and Okcabol, 2005).

The existing literature has predominantly focused on the role of accounting research in exploring the social construction of fraud (Choo and Tan, 2007; Dellaportas, 2013; Donegan and Ganon, 2008; M. Lokanan, 2018) and the individual morality of offenders in fraud cases (Gabbioneta et al., 2013; Morales et al., 2014; Murphy, 2012). However, the literature has often neglected the nuances of different financial crimes, such as money laundering, and the critical role of accounting in understanding how these crimes are perpetrated in sectors where accountants play a central role in handling financial transactions (Compin, 2008; Norton, 2018). The research to date examines the role of accountants as gatekeepers in preventing financial crimes (Compin, 2008; M. Lokanan, 2018; Mitchell et al., 1998). More specifically, this stream of research primarily analyzes the nature of financial crimes committed and assess the effectiveness of existing AML systems in detecting such acts (Amara et al., 2020; Compin, 2008; Norton, 2018; Ravenda et al., 2019; Sathye, 2024).

The broader question of the occupational culture and the socialization of how accountants represent themselves in the profession on AML matters is often minimized in this discourse. The present study builds on previous research and examines the contemporary role and practices of accountants and accounting firms in identifying and mitigating risks associated with money laundering in NBFIs. The findings show the important function of accountants as gatekeepers in both understanding and disrupting the networks and strategies used by individuals to anonymously launder or invest illicit funds in NBFIs. The study examines the effectiveness of current accounting practices in combating money laundering within Canada's NBFIs using script theory.

## 3. Script theory

Script theory is a psychological framework that explains human behavior as guided by internalized patterns, or scripts, that function as learned action programs for interpreting and responding to recurring situations (Schank and Abelson, 1975; Gilbert, 2024). These scripts, also described as event schemata, develop over time through education, professional training, and repeated exposure to institutional environments. They enable individuals to process information efficiently, anticipate expectations, and make decisions through rational evaluation of costs, risks, and outcomes (Choo, 1996; Kroneberg, 2014; van der Steen, 2009). Within professional contexts, scripts are shaped not only by individual experience but also by organizational norms, regulatory structures, and broader socio-institutional forces (Butler and Gannon, 2021; Yun and Roth, 2008).

Script theory conceptualizes individuals as deliberate and calculating actors whose behavior follows patterned sequences rather than ad hoc reactions. These patterns structure both cognition and communication, influencing how events are recalled, interpreted, and publicly narrated (Choo, 1989; Ekblom and Gill, 2016). In settings involving accountability or scrutiny, such as regulatory inquiries, scripts guide how professionals present their roles, justify decisions, and manage impressions in ways consistent with professional identity and institutional expectations (Schank, 1980; Schank and Abelson, 2013).

In the context of AML compliance, script theory provides a useful lens for understanding how accountants interpret their responsibilities and articulate their experiences. Script development unfolds across three interrelated stages of schemata. Preexisting schemata reflect accumulated professional knowledge, ethical standards, and regulatory familiarity that shape baseline perceptions of AML obligations (Yun and Roth, 2008). Assimilation integrates new information, such as emerging laundering typologies or regulatory reforms, into existing cognitive frameworks, often leading to procedural adaptation and reinterpretation of professional roles (Summers and Tudor, 2000). Accommodation occurs when persistent contradictions or institutional constraints require more substantive revision of scripts, prompting professionals to recalibrate expectations regarding effectiveness, responsibility, or enforcement capacity (van der Steen, 2009).

Witness testimonies offered during public inquiries can be understood as narrative performances of these scripts rather than neutral factual accounts. Such testimonies reflect how professional actors draw upon internalized scripts to frame actions, defend practices, and respond to perceived institutional pressures (Edwards et al., 2016; Ekblom and Gill, 2016). Linguistic tone becomes an important component of this performance. Scripts emphasizing professional competence, regulatory alignment, and institutional legitimacy tend to be enacted through confident and affirmative language. Scripts oriented toward procedural clarification or jurisdictional boundaries are more likely to generate neutral, technical discourse. Scripts that describe constraints, enforcement gaps, or role limitations often produce more critical or cautious language (Compin, 2008; Norton, 2018).

Sentiment is therefore not treated as emotion for its own sake but as an observable linguistic trace of script enactment under conditions of professional accountability and regulatory scrutiny. Sentiment analysis captures this affective–linguistic dimension, allowing systematic identification of patterned expressions that signal which professional scripts are dominant and when they are activated across different schema stages (Schank and Abelson, 1975; Yun and Roth, 2008). Integrating script theory with sentiment analysis enables a theoretically grounded interpretation of accountants' testimonies, linking computational text analysis to underlying cognitive and institutional processes shaping AML compliance narratives.

### 3.1. Sentiment analysis

Sentiment analysis is employed in this study not to infer subjective emotions in isolation, but to capture patterned affective–linguistic expressions through which professional scripts are enacted in public testimony. As an established task within NLP, sentiment analysis enables systematic identification of evaluative tone in text, commonly categorized as positive, neutral, or negative (Abercrombie and Batista-Navarro, 2020; Byrne et al., 2021). Prior research has applied sentiment analysis extensively across domains such as social media, customer reviews, and institutional discourse to identify structured patterns in language use (Lokanan, 2023). Within the present study, sentiment functions as an observable linguistic trace of how accountants perform professional scripts under conditions of regulatory scrutiny and institutional accountability.

The sentiment analysis literature identifies two primary methodological approaches: lexicon-based and machine learning–based techniques. Lexicon-based methods rely on predefined dictionaries that assign sentiment values to words or phrases. While providing portability across contexts, such approaches tend to generate sparse representations and are limited in their ability to capture contextual nuance, professional jargon, or institutional discourse (Ghiassi and Lee, 2018; Oliveira et al., 2014). These limitations become evident in regulatory and expert testimony, where meaning is often conveyed through technical language rather than overt emotional cues.

Machine learning approaches address these limitations by training supervised classifiers on labeled data, enabling models to learn domain-relevant sentiment patterns from contextual usage (Ghiassi and Lee, 2018; H. Zhang et al., 2014). Empirical evidence suggests that machine learning methods outperform lexicon-based approaches in capturing nuanced evaluative tone (Oliveira et al., 2014). However, their effectiveness may be constrained when applied across domains without retraining to account for domain-specific language and institutional context (Kennedy and Inkpen, 2006; M. E. Lokanan, 2023). These constraints have driven the growing adoption of deep learning techniques in sentiment analysis.

Deep learning models—including RNN+LSTM, CNN, and BERT—have demonstrated superior performance in capturing complex linguistic patterns and contextual dependencies in text (Alaparthi and Mishra, 2021; Lindén et al., 2023). Such models are particularly well suited to analyzing professional and regulatory discourse, where sentiment is often embedded in cautious phrasing, procedural framing, or implicit evaluative cues rather than explicit affect (Kute et al., 2021; M. Lokanan, 2023). In the context of AML compliance, deep learning–based sentiment analysis enables systematic identification of how accountants linguistically enact scripts emphasizing assurance, procedural neutrality, or institutional constraint, thereby complementing script theory by providing an empirical window into the affective–discursive dimension of professional testimony.

## 4. Research methodology

The data for this study was collected from two primary sources: in-depth interviews and sentiment analysis of testimonies from accountants at the Cullen Commission. The combination of these methods offers a holistic understanding of accountants' and other key stakeholders' perspectives on AML compliance, encompassing both challenges and responsibilities in preventing money laundering in NBFIs. The sentiment analysis of testimonies provides a quantitative exploration of attitudes and opinions, while the interviews offer qualitative insights, adding depth and context to the findings. The integration of these methods enables a more nuanced and validated understanding of the subjective experiences and opinions regarding money laundering practices within NBFIs.

### *4.1. Data source 1: interviews*

Interviews were selected as the key method for data collection to examine the intricate and experiential aspects of AML compliance. Given the complex and often clandestine nature of money laundering, especially in sectors like real estate, luxury vehicles, and gaming, first-hand accounts from professionals on the front lines provided valuable insights. By directly engaging with accountants and other key gatekeepers, the study sought to capture their detailed perspectives and first-hand experiences of AML compliance. These interviews offered a deep view into the challenges these professionals face, their perception of these challenges, and the strategies they employ to detect and report suspicious activities. Utilizing script theory as an interpretative lens, the interviews illustrate how accountants' actions and decisions in AML compliance follow established behavioral patterns, or "scripts", particularly in the realm of preventing financial crimes. The analysis reveals the scripted dynamics underlying the accountants’ testimonies to various compliance-related issues in the Commission’s inquiry.

#### *4.1.1. Sample*

Participants were selected using a combination of purposive and snowball sampling to capture a broad range of professional perspectives directly involved in AML compliance. Purposive sampling was used initially to identify individuals with relevant expertise across accounting, legal services, financial services, notaries, and regulatory bodies. Snowball sampling was subsequently employed to access additional participants within these professional and regulatory networks, where recruitment is often constrained by confidentiality obligations and the sensitive nature of financial crime work (Atkinson and Flint, 2001; Biernacki and Waldorf, 1981).

To reduce the risk of homogeneity associated with snowball sampling, recruitment was not limited to a single professional network. Outreach was expanded through professional platforms, including LinkedIn, where approximately 23 individuals across key AML-relevant sectors were contacted. By broadening recruitment beyond the authors’ immediate networks, the study gained access to a wider pool of participants and increased the diversity of professional roles and institutional perspectives represented in the sample.

Despite initial reluctance among some potential participants—particularly within legal and financial services—persistent recruitment efforts resulted in a diverse and information-rich sample. Data collection continued until thematic saturation was reached, with no substantively new themes appearing after the tenth to eleventh interview (Guest et al., 2006, 2020).As seen in Table 1, the final sample comprises 13 interviewees, including accountants, notaries, legal professionals, AML compliance experts, a parliamentarian, and a FINTRAC official. Participants’ professional experience ranged from 4 to 36 years. All accountants interviewed were currently working in, or had prior experience with, AML compliance. Notaries reported extensive collaboration with accountants in real estate–related AML matters. Government and regulatory participants collectively brought over three decades of experience in AML enforcement and policy. Interviews were conducted between 2019 and 2021. The diversity of professional roles and experience offered a multi-perspectival view of AML compliance practices within Canada’s non-banking financial institutions.

### *4.2. Data collection*

#### *4.2.1. Data source 1: interviewees*

All interviews for this study were conducted over the phone to accommodate the participants' schedules and locations. The interview format combined elements of semi-structured and unstructured approaches, allowing for both guided questions and open-ended discussions. The format enabled the collection of in-depth information while giving participants the flexibility to share their insights freely. Each interview was scheduled in the evening, outside of regular work hours, to ensure minimal disruption to the participants' professional commitments. The duration of the interviews varied, typically ranging from 45 min to an hour, providing sufficient time to explore the topics in depth without being overly time-consuming for the participants.

Following Becker's (1998) work on "Tricks of the Trade", interview questions were based on the "how" and the "what" rather than the "why" to provide space for the interviewees' expressions and their subjective experience about practices regarding AML compliance and AML regulations (Becker, 1998). Broadly speaking, the interviews were concentrated on two key questions: (1) What are the paradoxical tensions experienced by accountants and AML regulation in NBFI’s compliance? and (2) What are the relationships among these factors, and how do they manifest themselves in AML compliance? The approach seeks to uncover specific scenarios of AML navigation, including the effectiveness of accountants' roles in AML compliance, their perceptions and experiences, challenges faced, strategies employed in identifying and reporting

**Table 1**
Characteristics of Interviewees.

| Interviewees | Occupation | Experience (years) |
|---|---|---|
| A1 | Accountant | 4 |
| A2 | Accountant | 12 |
| A3 | Accountant | 15 |
| A4 | Accountant | 7 |
| A5 | Accountant | 14 |
| A6 | Accountant | 6 |
| A7 | Accountant | 17 |
| N1 | Lawyer and Notary | 36 |
| N2 | Notary | 6 |
| P1 | Parliamentarian | 18 |
| F1 | FINTRAC Official | 15 |
| F2 | Financial Services | 16 |
| L1 | Lawyer | 21 |

suspicious transactions, and the scripted nature of their actions in AML compliance.

#### 4.2.2. Coding interview data

The interview data was analyzed using ATLAS.ti to uncover common themes in the participants' responses. ATLAS.ti is a qualitative data analysis software that is widely used by researchers in various fields to analyze complex qualitative data. It is a powerful tool for organizing, coding, and analyzing text, audio, video, and graphical data. To code the transcript for analysis, we initially conducted open coding to identify key concepts and ideas in the data. Line-by-line coding was applied for each interview to identify the key themes that emerged. These themes were then organized into categories and subcategories to create a preliminary codebook. Table 2 shows the initial number of codes and subthemes that were generated through this process.

The next step was to review the codes and sub-themes from each interview to create attributional clusters that would help understand the patterns and relationships between different themes. The review process involved grouping similar sub-themes together and examining the connections between them. Using ATLAS.ti, the related sub-themes were then merged into representative themes. These new clusters represent the main themes from the interviews and serve as the basis for further analysis. From these emergent themes, we were able to gain insights into the experiences, perspectives, and challenges faced by professional accountants and other gatekeepers working in AML compliance. The final sets of themes represented two core discourses.

The first set of discourse is attributional and focuses on examining the underlying causes and factors contributing to money laundering. These discourses are problematized and defined in conceptual frames informed by the following attributional clusters relating to the accounting profession in the context of AML compliance: balancing accounting duties with AML compliance; the role of accounting in fraud detection and money laundering transactions; and the importance of documentation and transparency in AML compliance.

The second set of discourse is interpretive, focusing on the subjective experiences and perceptions of the interviewees and their involvement in AML compliance. Similar to the attributional discourse, the interpretative discourses are structured around thematic clusters related to the personal experiences and perspectives of participants in the context of AML compliance. These can be consolidated into four primary themes: accountants' knowledge and understanding of the AML framework; specific financial activities and ethical challenges faced by professionals; professional responsibilities and AML compliance; and the role of government in AML compliance and regulation. Fig. 1 presents a hierarchical structure that organizes and illustrates the relationships between the main ideas, themes, and sub-themes related to the accounting profession within the context of AML compliance. Note from Fig. 1 how these themes are interconnected and their relevance to the field of accounting in adhering to AML regulations.

**Table 2**
Codes and Sub-themes from Interviews.

| Interviewees | Codes | Sub-themes |
|---|---|---|
| A1 | 45 | 13 |
| A2 | 41 | 14 |
| A3 | 56 | 14 |
| A4 | 81 | 37 |
| A5 | 27 | 9 |
| A6 | 66 | 30 |
| A7 | 71 | 27 |
| N1 | 97 | 37 |
| N2 | 57 | 35 |
| P1 | 107 | 39 |
| F1 | 94 | 48 |
| F2 | 34 | 18 |
| L1 | 58 | 15 |

### 4.3. Ethical considerations

Ethical consents were obtained following the guidelines and protocols set by the University Ethics Office to ensure the protection of participants' confidentiality and anonymity throughout the study. Informed consent was obtained from all participants before conducting the interviews. Participants were informed about the study's purpose, their rights as participants, and how their responses would be used and reported. As this is a sensitive topic, measures were taken to ensure participants' anonymity and confidentiality. These measures included assigning pseudonyms to participants, refraining from collecting or reporting personal identifying information, and securely storing all interview data. Privacy and confidentiality were of utmost importance to establish trust and openness among participants when sharing their experiences and perspectives on AML compliance. The data was transferred to a password-protected computer accessible only to the research team. To further safeguard the data, we backed it up on an external hard drive and secured it in a locked cabinet drawer in the principal researchers' office.

### 4.4. Data source 2: sentiment analysis of witnesses' testimonies

Data were also drawn from the testimonies of accountants who appeared as witnesses before the Cullen Commission. The inquiry into money laundering in British Columbia spanned 133 days of hearings and involved 199 witnesses, with an additional 23 sworn affidavits. Witnesses represented a wide range of sectors, including legal services, financial institutions, regulators, and professional service firms. Among these, eight witnesses represented the accounting profession and provided testimony directly related to AML compliance. These eight testimonies constitute the full population of accounting professionals who testified on AML matters before the Commission and were therefore included in the analysis.

The analytical focus on eight accountant testimonies reflects the institutional structure of the inquiry rather than a sampling choice by the authors. As the Cullen Commission limited formal accounting-related evidence to these witnesses, the dataset captures the complete set of public, sworn testimonies through which the accounting profession articulated its role in AML compliance within the inquiry. While the number of testimonies is necessarily small, the witnesses occupied senior professional and regulatory positions and represented key accounting bodies and firms involved in AML governance. Accordingly, the findings are not intended to be statistically generalizable to all accountants but are analytically generalizable to the professional scripts and institutional narratives through which the accounting profession publicly represented its AML role in a major public inquiry. The sentiment analysis is therefore interpreted as an examination of discursive patterns within this bounded institutional setting, complemented by interview data to enhance contextual depth. Table 3 summarizes the demographics of accountants who testified at the Cullen Commission.

The main issue that accountants were asked to testify on during the Cullen Commission was focused on their role in *preventing and addressing money laundering within their respective jurisdictions and professions*. This role relates to the "extent, growth, evolution, and methods of laundering" in professional services, specifically focusing on the accounting sector (Cullen, 2022a). The accountants were questioned on the efforts and measures taken by the CPA profession in Canada to prevent and address money laundering activities. Using Python programming language, the sentiment analysis was conducted on the accountants' responses to the efforts and measures taken by the CPA profession in Canada to prevent and address money laundering. While sentiment analysis is mostly carried out at the sentence or aspect level (e.g., a tweet or a review), we segment the transcripts for analysis, including breaking them down into sub-sentences and aggregating the sentiments over the entire corpus (Abercrombie and Batista-Navarro, 2020).

The integration of interviews and sentiment analysis of witness

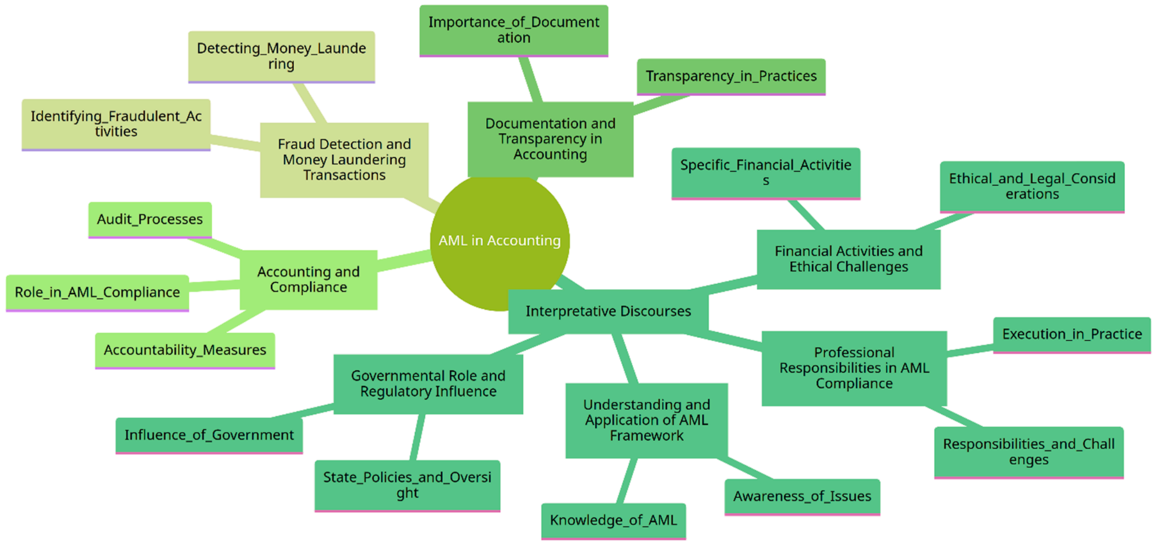


**Fig. 1.** Interconnection of Main Themes.

**Table 3**
Accountants who testified at the Cullen Commission on AML Compliance.

| Witnesses | Designation | Representation | Title | Experience (yrs)[a] |
|---|---|---|---|---|
| CPA1 | CPA/ ACAMS | Private Company | Consultant | 15 |
| CPA2 | CPA | CPABC | VP, Professional Conduct | 19 |
| CPA3 | CPA | CPABC | VP, Regulation | 3 |
| CPA4 | CPA | CPA Canada | VP, Regulatory Affairs | 4 |
| CPA5 | CPA | CPA Canada | Advisory Committee | 11 |
| CPA6 | CMA/CFE | Deloitte | Partner, Financial Crime | 24 |
| CPA7 | CPA/CFE | Deloitte | Regional Market Leader, Financial Advisory | 25 |
| CPA8 | CPA/ ACAMS | Ernst & Young | Senior Manager, Forensic | 13 |

[a] Experience are measures base on the years spent in their current roles and its relation to AML compliance.

testimonies on the role of accounting in AML compliance presents a unique opportunity to merge qualitative insights with quantitative data. This approach allows for an effective connection between the rich, nuanced information obtained from personal interviews and the broader, quantifiable sentiments derived from witness testimonies, thereby offering a more comprehensive and multifaceted understanding of the role of accounting in AML compliance. Linking the themes from the interview with sentiments from witnesses' testimonies shows how subjective perceptions and feelings align with specific thematic areas of concern or interest. We adopt an approach where the interviews provide further insights into the accountants' testimonies and sentiments, allowing for a deeper exploration and validation of the quantitative findings.

Sentiment analysis may be subject to misclassification in contexts where meaning is conveyed through sarcasm, irony, or highly specialized professional language. Such risks are particularly relevant in regulatory and expert testimony, where evaluative positions are often expressed implicitly through cautious or technical phrasing rather than overt affect (Kennedy and Inkpen, 2006; M. E. Lokanan, 2023). To address this limitation, the analysis relied on multiple machine and deep learning models and was triangulated with qualitative interview data, allowing sentiment patterns to be interpreted in relation to substantive themes rather than as standalone indicators.

#### *4.4.1. Data cleaning*

In NLP, data cleaning is a critical step, especially given that raw text data often contains noise and inconsistencies. The text cleanup process is crucial for transforming raw text into a format that is more conducive to NLP tasks like sentiment analysis and text classification. In this paper, we undertook several critical steps to transform the data for sentiment analysis. Firstly, we converted all text to lowercase, which significantly simplified processing by reducing the complexity of the data. Next, we removed punctuation marks, streamlining the data, and aiding in its simplification. We also identified and eliminated common stop words like "the," "an," and "a," which, while frequently used, add little overall meaning, and unnecessarily complicate the data. Further, we employed techniques of stemming or lemmatization to break words down to their base or root forms, thereby minimizing data complexity. Special characters such as "&," "#," and "%" were either removed or replaced, contributing to the overall data cleaning process. Lastly, we removed excessive white spaces to enhance the consistency and readability of the data. These procedures were essential for standardizing the text data, making it more manageable and effective for various NLP applications. The extent and manner of each step were selected based on the specific requirements of our NLP tasks and the characteristics of the raw text data under analysis.

#### *4.4.2. Subjectivity and polarity*

Sentiment analysis was used to analyze the text based on two important metrics: subjectivity and polarity. Subjectivity is an important component in sentiment analysis and captures the personal opinions and perspectives within a text (M. E. Lokanan, 2023). The subjectivity of the data ranges from 0 to 1, with 0 indicating objective and factual information and 1 indicating highly subjective and opinionated content (M. E. Lokanan, 2023; Pang and Lee, 2004). There are several methods to model subjectivity in text analysis. Lexicon-based methods use predefined lists of words, each assigned a sentiment score, to categorize text as either subjective or objective. Machine learning models, on the other hand, rely on training classifiers with labeled data to predict a text's subjectivity. Deep learning models utilize neural networks to learn from the input text and determine its subjectivity.

Polarity in sentiment analysis refers to identifying whether a piece of text conveys a positive or negative sentiment (Lindén et al., 2023; Pang and Lee, 2004). Binary classification is commonly used to determine whether the sentiment expressed is positive or negative. The polarity score of a text can range from $-1$ to $+1$, with $-1$ representing extreme negativity, $+1$ representing extreme positivity, and 0 representing neutrality (M. E. Lokanan, 2023; Pang and Lee, 2004). There are several techniques for modeling polarity. Lexicon-based methods utilize a pre-established list of words tagged with sentiment scores to categorize text as positive or negative. In machine learning models, classifiers are trained on datasets with labeled sentiments to accurately predict the polarity of new texts (Alaparthi and Mishra, 2021; M. Lokanan, 2023). Deep learning models, employing neural networks, learn from the nuances of input text to discern and predict its polarity (Kute et al., 2021; M. Lokanan, 2023; Smith et al., 2020). These approaches differ in complexity but share the goal of accurately assessing sentiment in text.

### 4.5. Text representation techniques

#### 4.5.1. Bag of words

The Bag of Words (BoW) method is a simple yet effective technique for representing text data in NLP. The method transforms text into a collection (or "bag") of its words while ignoring the sequence, grammatical structure, and context of those words (Y. Zhang et al., 2010). The BoW model constructs a vocabulary containing all unique words across the text corpus and then represents each document as a vector based on word frequency (Zhao and Mao, 2018). Under this approach, each position in the vector corresponds to a word from the vocabulary, and the value represents the number of times that word appears in the document. BoW treats each word independently and does not consider relationships between words (Y. Zhang et al., 2010; Zhao and Mao, 2018).

The first step in implementing BoW is to construct a vocabulary comprising all unique words across the text corpus. Each word is then assigned a distinct index. Next, each document is converted into a vector of word frequencies. The vector has the same length as the vocabulary, and each element reflects the frequency of the corresponding word in the text. If a word does not appear in the document, its count is set to zero (Y. Zhang et al., 2010; Zhao and Mao, 2018). Mathematically, BoW is represented as follows:

For a document $d$ in a corpus of $N$ documents, let:

- $V = \{w_1, w_2, \ldots, w_m\}$ be the vocabulary (unique words across all documents).
- $f(w_i, d)$ be the frequency of word $w_i$ in document $d$

Each document is represented as a vector:

$$d = [f(w_1, d), f(w_2, d), \ldots, f(w_m, d)]$$

where:

- Each element represents the word count of a specific word $w_i$ in document $d$.
- If a word is absent, its count is 0.

Thus, the BoW representation for a document simply counts word occurrences without considering word order or meaning.

#### 4.5.2. Term frequency-inverse document frequency (TFIDF)

Term Frequency-Inverse Document Frequency (TF-IDF) is a statistical technique frequently employed in NLP for information retrieval and text analysis. The primary objective of TF-IDF is to assess the significance of a word within a document or a larger collection of texts (corpus) by considering two key factors: its frequency within the document and its rarity across the corpus (Havrlant and Kreinovich, 2017; M. E. Lokanan, 2023). In NLP, the TfidfVectorizer serves as a valuable tool to transform a set of raw documents into a matrix of TF-IDF features. The process involves two main steps:

1. **Tokenization**: The initial raw text is broken down into individual tokens or words. These tokens are then processed and converted into numerical representations.
2. **TF-IDF weighting**: For each token, two values are computed. First, its term frequency (TF) within the specific document is calculated. Second, the inverse document frequency (IDF) is determined, taking into account how frequently the token appears across all documents in the corpus. The final TF-IDF score for a token is obtained by multiplying its TF and IDF values. The formula for TF-IDF is expressed as follows:

$$\mathrm{TF-IDF}(t, d) = \mathrm{TF}(t, d) \times \mathrm{IDF}(t)$$

Where,

$\mathrm{TF}(t, d)$: (Term Frequency) → Measures how often term $t$ appears in document $d$:

$$\mathrm{TF}(t, d) = \frac{\text{Number of times } t \text{ appears in } d}{\text{Total number of words in } d}$$

$\mathrm{IDF}(t)$: (Inverse Document Frequency) → Measures how unique or important term $t$ is across all documents:

$$\mathrm{IDF}(t) = \log\left(\frac{N}{DF(t)}\right)$$

where:

- $N$ = Total number of documents.
- $DF(t)$ = Number of documents containing term $t$.

The resulting TF-IDF matrix is a versatile resource used in various NLP tasks, including text classification, text clustering, and topic modeling. TF-IDF weighting is a favored text representation technique because it can effectively capture the importance of a word within a document while diminishing the influence of terms that are common throughout the entire corpus (Havrlant and Kreinovich, 2017; Kumar and Subba, 2020; M. E. Lokanan, 2023). Fig. 2 illustrates the NLP workflow from raw data to the sentiment analysis.

### 4.6. Algorithms and performance measures

Both machine and advanced deep learning algorithms were considered for sentiment analysis. The machine learning algorithms include Naïve Bayes, Support Vector Machines (SVM), and Random Forest, while the deep learning algorithms include RNN+LSTM, CNN, and BERT-based Models. These algorithms were chosen based on their proven effectiveness in sentiment analysis tasks and their ability to efficiently handle large amounts of text data (Alaparthi and Mishra, 2021; Liao et al., 2017; M. E. Lokanan, 2023; Vathsala and Holi, 2020). In selecting and evaluating these algorithms, considerations were given to their accuracy, scalability, robustness, and interpretability. The algorithms were evaluated based on their ability to accurately classify text sentiments, effectively handle large volumes of data, maintain performance in various scenarios, and adapt to evolving language patterns and contexts.

The metrics used to evaluate the performance of these algorithms are accuracy, precision, recall, and F1-score. Table 4 provides the formula for these performance measures. Accuracy reflects the proportion of correctly classified instances among all instances, precision reflects the proportion of correctly classified positive instances among all instances classified as positive, recall reflects the proportion of correctly classified positive instances among all actual positive instances, and F1-score represents the harmonic mean of precision and recall.

Where:

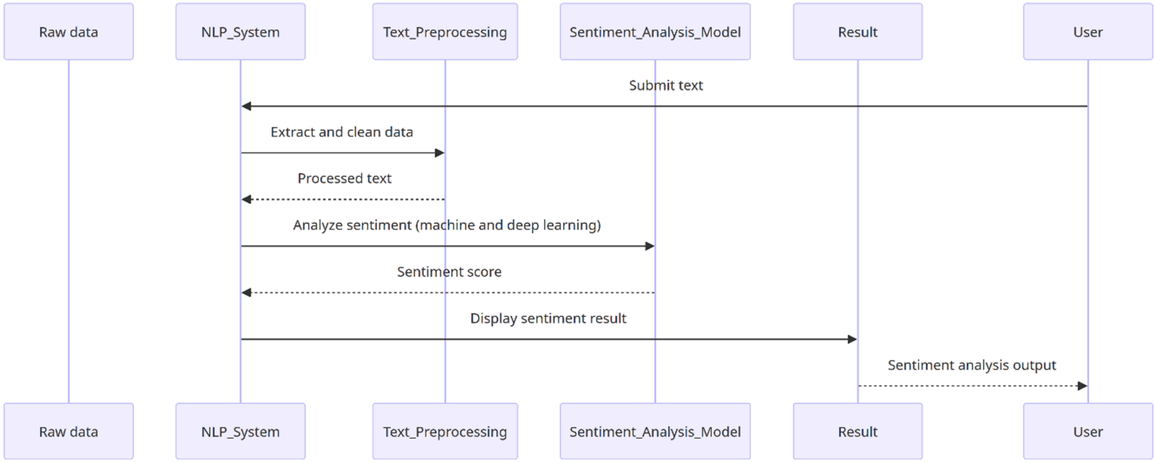


**Fig. 2.** NLP Workflow.

**Table 4**
Performance Metric.

| Metric | Formula |
|---|---|
| Accuracy | TP+TN/TP+TN+FP+FN |
| Precision | TP/TP+FP |
| Recall | TP/TP+FN |
| F1Score | 2 ×*Precision*+*Recal* / *Precision* × *Recall* |

- **TP** (True Positives): The number of positive instances correctly classified as positive.
- **TN** (True Negatives): The number of negative instances correctly classified as negative.
- **FP** (False Positives): The number of negative instances incorrectly classified as positive.
- **FN** (False Negatives): The number of positive instances incorrectly classified as negative.

## 5. Machine and deep learning models for sentiment analysis in AML compliance

### 5.1. Sentiment analysis

Fig. 3 displays the sentiments from the accountants' testimonies at the Cullen Commission inquiry. The results indicate a predominance of positive sentiments, accounting for approximately 46 % of the content. The high proportion of positive sentiment suggests that a significant portion of the testimonies conveyed optimism or confidence, likely reflecting satisfaction with regulatory frameworks, compliance procedures, and involvement in AML initiatives. The neutral sentiments, while the smallest category, constituted about 12 % of the testimonies and reflect content presented in a factual and unbiased manner, focusing on straightforward descriptions of procedures and regulations. The negative sentiment comprises 44 % of the content and highlights areas of concern or challenges faced, possibly relating to the effectiveness of current AML measures or potential regulatory gaps in legislation. Overall, the sentiment analysis indicates that the accountants' testimonies to the Commission were largely positive or negative, with fewer neutral sentiments.

#### 5.1.1. *Results from machine learning classifier*

Table 5 displays the performance of the machine learning classifier in predicting the sentiments of accountants who testified at the Cullen commission. The Gaussian Naïve Bayes (GaussianNB) model demonstrated strong and consistent performance across both the TF-IDF and BoW methods, with high accuracy and F1-scores in the training and testing data. The results suggest that GaussianNB models were effectively able to capture the nuances of the accountants' responses on AML compliance, possibly due to the probabilistic nature of the model, which aligns well with the textual data patterns in the testimonies (see W.

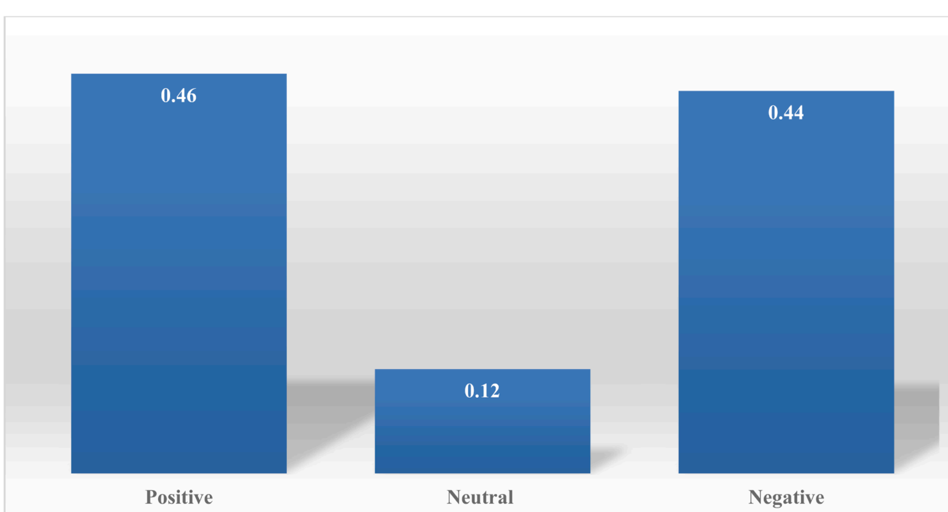


**Fig. 3.** Sentiment Analysis.

**Table 5**
Machine Learning Model Performance.

| Model Type | Accuracy | Precision | Recall | F-1-Score |
|---|---|---|---|---|
| GaussianNB Train TFIDF | 0.93 | 1.00 | 0.86 | 0.93 |
| GaussianNB Test TFIDF | 0.81 | 0.82 | 0.84 | 0.83 |
| GaussianNB Train BOW | 0.93 | 1.00 | 0.86 | 0.93 |
| GaussianNB Test BOW | 0.82 | 0.82 | 0.84 | 0.83 |
| Random Forest Train TFIDF | 0.89 | 1.00 | 0.80 | 0.89 |
| Random Forest Test TFIDF | 0.79 | 0.86 | 0.72 | 0.79 |
| Random Forest Train BOW | 0.86 | 1.00 | 0.74 | 0.85 |
| Random Forest Test BOW | 0.77 | 0.86 | 0.68 | 0.76 |
| SVM Train TFIDF | 0.49 | 0.94 | 0.14 | 0.24 |
| SVM Test TFIDF | 0.46 | 0.90 | 0.11 | 0.20 |
| SVM Train BOW | 1.00 | 0.99 | 1.00 | 1.00 |
| SVM Test BOW | 0.90 | 0.91 | 0.89 | 0.90 |

Zhang and Gao, 2011).

The Random Forest classifier showed good results on the training set but a notable decrease in performance on the test set, particularly with the BoW approach. The decline in recall and F1-score indicates that the Random Forest model may be overfitting to the training data, reducing its ability to generalize to unseen testimonies. Such a pattern implies that although the model captures sentiment structures in the training data, it struggles to maintain comparable performance when applied to new, varied responses.

The SVM classifier presented a stark contrast between its performance with TF-IDF and BoW. For TF-IDF, SVM performed poorly on both the training and testing sets, suggesting a mismatch between the model's assumptions and the distribution of the testimony data, which limited its effectiveness in analyzing sentiments related to AML compliance in the accounting profession. However, with BoW, SVM achieved perfect scores on the training data and very high scores on the test data, indicating that when paired with BoW, SVM generalized well and effectively discerned the sentiment expressed in the accountants' testimonies.

In the context of the accountants' testimonies on AML compliance, the models' ability to distinguish between positive, neutral, and negative sentiments is crucial. A model that overfits may not capture the subtleties of real-world testimonies, which can vary greatly in sentiment due to the complexity of AML issues. GaussianNB demonstrates the best balance in this regard, maintaining strong performance without overfitting. SVM paired with BoW also demonstrates strong generalization capabilities, a feature that is valuable for interpreting varied testimonial data.

#### 5.1.2. *Deep Learning Classifier*

Table 6 displays the results of the deep learning models. The performance metrics indicate that deep learning models—CNN and RNN+LSTM—outperform traditional machine learning classifiers in sentiment analysis, reflecting their superior ability to capture the nuances of textual data. CNN's high-test scores suggest effective learning and generalization, despite the potential overfitting indicated by perfect training scores. RNN+LSTM's slightly lower test scores, compared to CNN, demonstrate strong capabilities in sequential data understanding, a feature that is central to sentiment analysis. While showing lower performance on training data, the BERT model indicates potential underfitting or the need for more extensive training and shows improved generalization on the test data. The overall pattern highlights BERT's ability to understand complex language structures, though it does not achieve the high performance levels demonstrated by the CNN and RNN+LSTM models (see also Alaparthi and Mishra, 2021; M. Lokanan, 2023).

**Table 6**
Deep Learning Model Performance Metrics.

| Model Type | Accuracy | Precision | Recall | F-1-Score |
|---|---|---|---|---|
| CNN Model Train | 1.00 | 1.00 | 1.00 | 1.00 |
| CNN Model Test | 0.92 | 0.93 | 0.93 | 0.93 |
| RNN+LSTM Model Train | 0.96 | 0.98 | 1.00 | 0.99 |
| RNN+ LSTM Model Test | 0.88 | 0.91 | 0.91 | 0.91 |
| BERT Model Train | 0.67 | 0.62 | 0.80 | 0.70 |
| BERT Model Test | 0.71 | 0.67 | 0.83 | 0.74 |

### 5.2. *Analysis of the Sentiments*

#### 5.2.1. *Positive Sentiments: Adherence to Regulatory Frameworks and Compliance Procedures*

Integrating the positive sentiments expressed by accounting professionals in their testimonies with insights from interviews provides a comprehensive picture of the accounting profession's commitment to AML compliance. The testimonies, as presented in Table 7, highlight the robustness of the regulatory framework governing the accounting profession. CPA 2, for instance, underscores the strength of this framework, noting the involvement of CPA Canada in the federal AML regime, thereby connecting the profession directly with national AML efforts. A similar sentiment appears in the proactive measures advocated by CPA 4, who emphasizes the importance of suspicious transaction reporting and the potential role of whistleblowing regimes, indicating a forward-thinking approach to compliance (see Norton, 2018).

The positive sentiments align with the perspectives shared by interviewees, including FINTRAC officials and seasoned accountants. As a FINTRAC official pointed out, accountants and accounting firms are not just responsible for maintaining financial records but also play a crucial role in law enforcement investigations by providing financial transaction reports and implementing compliance programs:

> Accountants and accounting firms are responsible for providing FINTRAC with certain financial transaction reports, for implementing a compliance program and for keeping records that may be required for law enforcement investigations. Their obligations under the PCMLTFA and associated Regulations are described on FINTRAC's web page. (F1)

Such obligations underscore the integral role accountants play in safeguarding economic integrity and preventing the misuse of Canada's financial systems for money laundering activities.

Furthermore, insights from an accountant with expertise in white-collar crime (A1) and another with extensive experience in AML compliance (A7) reveal the depth of professional responsibility and the practical challenges involved in AML compliance:

**Table 7**
Excerpts of Positive Sentiments.

| Sentiments | Excerpts |
|---|---|
| **Positive** | "Our regulatory framework we believe is very strong and, you know, in terms of professional conduct, our code of professional conduct has five or six rules that would capture money laundering activities …CPA Canada has been very much involved with the federal anti-money laundering program regime and so as part of CPA Canada we have been through CPA Canada sort of involved or connected to the issues." CPA 2<br>"From a tax compliance perspective, it's absolutely necessary [for accountants] to be able to understand how …corporation interact across borders… because, you know, tax compliance is one of the weak spots of any organized crime network." CPA 1<br>"We need to feed information to law enforcement, whether it's through suspicious transaction reporting or otherwise. So, we suggested that compliance programs as a whole are our key element but also 8 the whistle-blowing regime." CPA 4<br>"…our code of professional conduct has five or six rules that would capture money laundering activities. We have a rule 213 which is called unlawful activity, and this is more than a discouragement. This is a prohibition on members against being involved with unlawful activity that they know to be unlawful or should know to be unlawful. So that's one example of the rules." CPA 3 |

> …if you are not disclosing something for a private client…that is not something that is on you. But if you are doing an audit…then you will have questions coming up to you with the CPA board. This approach is essential in assessing fraud risk, as they added, "Everything works on estimates and ratios…If something cracks one time, we are saying that within reasonable investigation we haven't found any red flags of fraud. Not that we guarantee there is no kinds of fraud. (A1)

The testimony from A1 illustrates the differentiation in accountability between private client disclosures and audit engagements, highlighting the high stakes and rigorous scrutiny involved in the latter. Building on A1's insights into the different levels of accountability in private client disclosures and audit engagements, the comments from Accountant A7 delve further into the practical aspects of compliance:

> Let me give you in the context of an accountant. I think there has been two or three suspicious transactions reported by all accountants over time… They further detailed the complexities of filing STRs, emphasizing the challenge in Section g and Section h of the STR form. Section g is the narrative where you describe what the situation was like…many will just say, listen FINTRAC, you told me that if this happened it would be an indication of suspicion, so I'm going to tell you that's what I saw. This approach minimizes conflict with clients by sticking to objective indicators of suspicious activities. (A7)

A7 provides a real-world perspective on the complexities of filing STRs, demonstrating the nuanced decision-making that accountants must navigate in their compliance efforts.

The sentiments from the accountants' testimonies and the insights from interviews paint a positive picture of the accounting profession's critical role in AML compliance. The strength of the regulatory framework, as emphasized by CPA 2, coupled with proactive measures like STR and whistleblowing regimes, underlines a forward-thinking and robust approach to compliance within the profession (Compin, 2008; Norton, 2018). The input from FINTRAC officials further cements the pivotal role of accountants in maintaining financial transparency and aiding law enforcement efforts, showcasing their essential contribution to safeguarding Canada's NBFIs from criminal networks. The detailed insights provided by the accountant with expertise in white-collar crime and AML compliance reveal the depth of professional responsibility that characterizes the field (see Amara et al., 2020; Mitchell et al., 1998; Ravenda et al., 2019). The differentiation in accountability between private client disclosures and audit engagements, as highlighted by A1, underscores the high stakes involved in these roles (example see Gabbioneta et al., 2013; Power, 2013). The practical challenges and complex decision-making involved in filing STRs, as discussed by A7, further illustrate the complexity of the compliance landscape that accountants navigate (Amara et al., 2020).

### 5.2.2. *Neutral sentiments: proactive measures and future commitment to AML compliance*

An examination of the neutral sentiments expressed in the accountants' testimonies highlights both convergences and divergences in viewpoints when compared with the insights provided by interviewees on the accounting profession's involvement in AML compliance. As seen in Table 8, the neutral sentiments from the testimonies highlight plans for future engagement, ongoing monitoring, and continuous improvement in AML strategies. CPA 3 acknowledges CPABC's focus on equipping members with resources despite not being direct regulators of money laundering, while CPA 8 and CPA 7 discuss specific strategies and tools employed in the real estate sector and B.C. casinos, for example, to detect money laundering activities. Similar to prior research in this area, these testimonies reflect a proactive, albeit impartial, approach to AML compliance, focusing on practical measures and resources (Amara et al., 2020; Compin, 2008; Norton, 2018).

In contrast, the interviews with professionals and gatekeepers of AML compliance reveal a more nuanced and critical view of the accounting profession's involvement in AML activities. One professional accountant points out the infrequency of compliance reviews and audits in the accounting industry, suggesting a gap between regulatory expectations and actual practices:

**Table 8**
Excerpts of Neutral Sentiments.

| Sentiments | Excerpts |
|---|---|
| **Neutral** | "But it should be noted that our focus and our mandate of CPABC is not in the area of money laundering and as such we don't regulate specifically to this area. So what we do and what we're very conscious of is trying to provide as much resources to our members as we can to help them support them in meeting their needs." CPA 3<br>In response to patrons brining cash to B.C. casinos "We had provided the context of our analysis that showed that a small subsection of cheques were identified as part of this population and that it was a small subset of patrons involved in which we performed our analysis. I would say that the presentation was objective in nature in the terms of what we had identified as part of it without an opinionated response in terms of impact." CPA 8<br>For example, one of the money laundering typologies or financial crime typologies that we would look for in real estate is – within the province of BC would be to take information that is being provided to LTSA, for example, under the Land Ownership Transparency Registry about the beneficial ownership of property here in the province and – as a starting point, and therefore enable us to identify or whomever to identify, this platform to identify exactly those properties that are owned, for example, by numbered companies in the province. So any property, any condo, any commercial – sorry, any residential real estate property that is owned by a private company or a numbered company could be identified. CPA 7 |

> Internally, there is a compliance review and compliance audit every other year, so that's the enforcement and then there is examinations by FINTRAC, but I'll tell you in both cases in the accounting industry, there are very few accounting firms that conduct those examinations of those reviews every two years. And then there are seldom any accounting firms examined. (A7)

A similar concern emerges in the remarks of P1, a senior parliamentarian, who acknowledges the role of accountants in reporting suspicious transactions but expresses uncertainty about the effectiveness of these measures, particularly in the real estate sector. P1 also provides insight into the legislative background and expectations of accountants in AML compliance, indicating an awareness of these responsibilities among professionals:

> The accounting community was well-informed about this legislation, as they actively participated in the legislative process. They presented their views as witnesses before the Standing Committee on Finance. I was present during these sessions, so I can confirm their awareness and understanding of the legislation. Specifically, they lobbied to have Chartered Accountants excluded from certain attest functions during the legislative process, and this exclusion was ultimately accepted. (P1)

Additional perspective from A3 highlights limitations in the accountant's role in detecting money laundering in real estate, emphasizing the responsibility of lawyers in transactions involving large cash sums.

> From an anti-money laundering standpoint, accountants don't typically play a significant role in the real estate sector; that responsibility largely falls to lawyers. For example, in a real estate transaction, such as buying a house, the parts of the transaction involving mortgage proceeds are less likely to be associated with money laundering, as these funds come from financial institutions. However, the cash component of such transactions is more susceptible to money laundering risks. (A3)

A3 further stated that

> Let's say I'm buying a house for $500,000, with $100,000 of it being a cash deposit. This cash deposit will be transferred into my lawyer's trust account, which consolidates the total payment for the house. In this scenario, the lawyer bears the responsibility of scrutinizing how this cash payment is made. If I were to bring a suitcase with $100,000 in cash, this would immediately raise red flags for potential money laundering, given the unusual nature of such a large cash transaction. It's these kinds of scenarios, involving significant cash payments, where money laundering suspicions typically arise. Therefore, in real estate transactions, the onus of identifying and reporting potential money laundering activities often lies more with the lawyers handling the transactions rather than the accountants. (A3)

The distinction underlined by A3 highlights the specialized roles within AML efforts in real estate, suggesting a more collaborative approach between various professionals, where lawyers shoulder the primary responsibility for scrutinizing high-risk cash transactions, while accountants focus on other aspects of financial compliance.

N1, a senior notary, adds another dimension to this discussion by detailing the auditing processes and the standards for compliance in the notary profession. N1 explains,

> We conduct regular internal and external audits of our members, focusing on reporting suspicious transactions, maintaining customer records, and managing risk in compliance with the standards. However, a key challenge lies in understanding what constitutes a suspicious transaction.

Such a perspective reinforces the need for proactive measures and clear guidelines in AML compliance, aligning with the accountants' commitment to evolving AML strategies (Amara et al., 2020; Mitchell et al., 1998). Yet, A4 expresses concerns about the obstacles in AML reporting, such as limited information availability and the relatively new nature of these reporting standards, suggesting challenges in implementing consistent practices.

> Money laundering is typically conducted in a covert manner, making it challenging for people to detect or understand what is happening. One of the key challenges in identifying and reporting money laundering is the limited availability of information. Often, there's a reluctance from involved parties to provide necessary details. Additionally, the practice of reporting money laundering is relatively recent, which means there aren't as established or universally accepted standards for it as there are in traditional financial reporting. In financial reporting, we have clear, standardized guidelines that must be followed. In contrast, money laundering reporting tends to be more case-dependent, focusing on the specific information available or accessible in each individual scenario. (A4)

A4's remarks underscore the complexity of AML reporting and the variability that professionals must navigate when determining whether a transaction warrants suspicion.

While the neutral sentiments from the accountants' testimonies suggest a commitment to evolving AML efforts and a focus on practical compliance measures, the interviews reveal a more complex landscape. There are concerns about the frequency and effectiveness of compliance audits, the actual role of accountants in specific sectors like real estate, and challenges in the implementation of AML reporting standards (Bolgorian and Mayeli, 2020; Habib et al., 2020; Ravenda et al., 2019). These concerns point to a need for enhanced training, clearer guidelines, and perhaps more rigorous enforcement of compliance measures within the accounting profession to ensure more effective AML practices (Mitchell et al., 1998; Norton, 2018).

### *5.2.3. Negative sentiments: involvement in and prevention of Illegal activities*

Negative sentiment in the testimonies is most pronounced where accountants confront structural and regulatory constraints rather than individual compliance failures. As shown in Table 9, critical and cautious language emerges when professional scripts encounter role ambiguity, weak enforcement capacity, fragmented regulatory guidance, and reliance on client discretion. Script theory helps explain these patterns, as accountants enact scripts shaped by institutional boundaries and limited statutory authority, producing negative sentiment when expectations of effective AML oversight conflict with practical constraints. The patterns in Table 8 illustrate how such sentiments reflect systemic shortcomings embedded within the AML framework rather than resistance or indifference at the individual level.

The testimonies expressing negative sentiments raise critical concerns regarding the level of involvement of accountants in AML activities and the efficacy of the existing AML measures. These sentiments are further contextualized and expanded upon in the interviews, providing a more comprehensive understanding of the underlying issues and challenges. Table 10 suggests that professional accountants exhibit significant skepticism and an acute awareness of the limitations in their role in combating money laundering (see Amara et al., 2020; Compin, 2008; Norton, 2018). CPA 1 questions the changing nature of money laundering in relation to the sophistication of organizations involved, indicating a dynamic and evolving challenge. CPA 2 points out a significant observation: "We have not had any cases involving CPABC members or firms being involved or connected to money laundering or terrorist financing activities." These remarks may signal effective compliance practices or, alternatively, a gap in detection and reporting mechanisms. CPA 4 raises concerns about the low number of STRs, suggesting potential under-engagement in identifying suspicious activities. CPA 5 emphasizes the necessity of effective law enforcement and real consequences as deterrents, underscoring the need for stronger AML efforts.

These testimonies are echoed and expanded upon in the interviews. Accountant A7 provides an important perspective on the legislative framework governing AML compliance: "you can't expect the accountants who are the bad accountants, the ones that are actually helping to launder money to report on themselves." The remarks from A7 suggest that accountants, especially those who might be complicit in laundering activities, are unlikely to self-report due to a conflict of interest or professional bias (Amara et al., 2020; Mitchell et al., 1998). The concern is further compounded by the narrow definition of "accountant" in the current legislation, which might exclude certain practitioners from reporting requirements:

> …not all accountants in Canada are covered. If you look at the definition in the PCMLTFA, it defines accountant very narrow, is only people who hold certain designation. Funny enough, it still doesn't say that CPAs are covered. It seems that nobody is covered by the current legislation as worded. (A7)

Such legislative ambiguity may significantly weaken the effectiveness of AML measures in identifying and preventing money laundering activities (see Mitchell et al., 1998).

**Table 9**
Negative Sentiment and Structural/Regulatory Constraints in AML Compliance.

| Structural / Regulatory Issue | Script-Theoretic Interpretation | Illustrative Evidence |
|---|---|---|
| Overreliance on professional discretion | Discretion script shifts AML responsibility to clients | "Once a client says 'I will take responsibility,' you just roll that agreement forward." (A1) |
| Role ambiguity between accountants and lawyers | Jurisdictional boundary script reallocates AML duties | "The accountant does not have a role in fighting money laundering in real estate." (A3) |
| Weak enforcement and low detection risk | Rational calculation script normalizes non-compliance | "CRA can't audit everyone… it's an odds game." (A1, A7) |
| Lack of standardized guidance and training | Institutional fragmentation script reflects regulatory gaps | "We talked about ethics, but not money laundering… there's not much awareness." (A4, A6) |

**Table 10**
Excerpts of Negative Sentiments.

| Sentiments | Excerpts |
|---|---|
| **Negative** | "I don't think that that sentence says the extent of accountant money laundering involvement – in money laundering in Canada changes based on sophistication, but I would even agree if it were that limited. The point is that the ways that accountants launder money must – and adopting the broad definition of "accountant" must change based on the sophistication of the organization and must change based on the degree to which the organizations or activities are illegal." CPA 1<br>"We have not had any cases involving CPABC members or firms being involved or connected to money laundering or terrorist financing activities. We haven't received any information referrals from FINTRAC or any other regulatory body or any individual regarding any CPABC member or firm being involved, engaged, involved with, facilitating money laundering or terrorist financing activities and there's no evidence that there's a problem with CPAs in BC or in Canada." CPA 2<br>"When I look at the information – when you use the word "low," I also wouldn't want the [Suspicious Transaction Report] number to be high. And the reason I wouldn't want the number to be high is because I would not want to think that we've got member engaging in activities in such volume, triggering activities in such volume that they are seeing such numbers with respect to suspicious activity in relation to their work because it starts to make me question how did they accept the engagement in the first place to be involved." CPA 4<br>"There needs to be a real deterrence factor. Filing a suspicious transaction report with no consequences or not being able to bring a case, not being able to fine corporations, not being able to provide the incentives for a more enhanced compliance program for remediation. At the end of the day there needs to be a cost of crime; right? So, we can all do – employ all these great efforts, but we do need to strengthen law enforcement." CPA 5 |

These challenges are further expanded upon by the remarks of a senior FINTRAC personnel (F1), who emphasize the vital role of professional facilitators, including accountants, in maintaining transparency in economic activities. F1 highlights the role of professional facilitators in masking the origins of tainted funds. According to F1, "these compliance obligations allow for certain economic activities to be more transparent, which helps prevent and deter nefarious individuals and organizations from using Canada's legitimate economy to launder the proceeds of their crimes or finance terrorist activities." The statement underscores the pivotal role that transparency plays in safeguarding the integrity of the financial system.

F1's remarks also shed light on the dual role of professional facilitators, such as accountants, in the context of AML efforts. On the one hand, accountants are crucial gatekeepers for ensuring compliance with financial regulations and maintaining transparency in financial transactions. Their expertise and professional responsibilities place them in a unique position to detect and report suspicious activities. On the other hand, F1 acknowledges the potential for these professionals to be exploited or willingly participate in masking the origins of illicit funds. These remarks highlight a critical tension within the profession, where the skills and knowledge that enable accountants to contribute positively to financial integrity can also be used to subvert it (i.e., conceal the origins of illicit funds) (see Mitchell et al., 1998)

Expanding on the role of accounting in addressing money laundering challenges, the insights from a notary (N1) offer a distinctive perspective. N1 highlights the delicate balance accountants must strike between tax avoidance and tax planning, emphasizing the challenge faced by the accounting industry. "While accountants don't directly handle money, their involvement in tax planning schemes and the structures they set up play a crucial role in financial transactions" (N1). The distinction between legitimate tax planning and illegal tax avoidance is a significant concern, as anti-avoidance rules are in place to prevent illegal practices. N1 also touches upon instances where accountants may act as trustees, potentially obscuring the true ownership of assets. These observations underscore the importance of sworn declarations and solid evidence to effectively combat such practices, highlighting the critical role accountants play in ensuring transparency and compliance within financial transactions (Amara et al., 2020; Gabbioneta et al., 2013; Mitchell et al., 1998).

The negative sentiments expressed by some accountants echo the concerns that existed when AML legislation was introduced in Canada. As P1 highlighted, there were apprehensions within the Chartered Accountants (CAs), who later became CPAs, about their obligations under the legislation.

> When we brought in the anti-money laundering legislation… the CA at the time were quite concerned… whether they would be required under the legislation to report their suspicions to FINTRAC… but that they were still responsible for reporting to FINTRAC any suspicious transactions that occurred, you know, the normal course in their professional practice. (P1)

The concerns revolved around whether accountants would be required to report suspicious transactions to FINTRAC during normal audits, potentially complicating their professional roles. To address these concerns, regulations were introduced to clarify that CPAs would not be required to report suspicions arising during routine audits. However, they remained responsible for reporting any suspicious transactions encountered in the normal course of their professional practice. The context narrated by P1 indicates that while initial apprehensions were present, the regulatory framework sought to strike a balance between accountants' professional responsibilities and the need for AML compliance. The framework also makes clear that accountants, like real estate agents or brokers, are obliged to report suspicious transactions when they are part of or parties to a transaction. Such requirements, although not foolproof, function as mechanisms to support compliance and deter misconduct(Amara et al., 2020; Bolgorian and Mayeli, 2020; Norton, 2018).

## 6. Discussion and analysis

### *6.1. Understanding accountant testimonies in AML compliance through script theory*

The application of script theory to testimonies suggests that internalized scripts significantly influence how accountants recall and present events, impacting the accuracy and consistency of their testimonies (Choo, 1989, 1996; Gilbert, 2024; van der Steen, 2009). In AML compliance, these cognitive scripts appear to shape accountants' perceptions and actions in facing professional challenges. The results of the sentiment analysis conducted through machine and deep learning models corroborate these findings with high performance accuracy, revealing accountants' sentiments towards upholding financial transparency and preventing money laundering in Canada's NBFIs. The next section examines the influence of cognitive scripts on the testimonies of accountants at the Cullen Commission and their role in AML compliance within NBFIs through the different stages of schemata: preexisting, assimilation, and accommodation.

#### *6.1.1. Preexisting schemata: foundations of script development in AML knowledge*

Preexisting schemas involve acquired knowledge, beliefs, prior experiences, education and training in AML, and initial perceptions and interpretations that individuals bring into the professional realm of regulation and compliance. These scripts are not static; they are dynamic constructs that evolve over time through continuous learning and exposure to new information and regulatory changes (R. Schank and Abelson, 1975; Yun and Roth, 2008). The results from the sentiment analysis suggest that the accountants' testimonies are influenced by their knowledge and engagement with AML compliance. While the analysis identifies varying sentiments, it's important to view these as part of a spectrum rather than discrete categories. Each sentiment reflects a different aspect of the accountants' cognitive scripts towards AML compliance.

The positive sentiments, for instance, highlight a script that values strict adherence to regulatory frameworks and compliance procedures. These findings corroborate previous results that suggest that script is likely influenced by formal training and an understanding of the critical role of accountants in maintaining financial integrity (Choo, 1989, 1996; van der Steen, 2009). The positive sentiments showcase a commitment to upholding the principles of AML compliance, shaped by their preexisting schemas of professional responsibility and ethical standards. Conversely, the more cautious or skeptical views, which might be categorized as neutral or negative sentiments, reflect scripts that are shaped by practical experiences and perhaps by encounters with the complexities and challenges in AML compliance. These scripts may emphasize the need for continuous adaptation and improvement in AML strategies, recognizing the dynamic nature of money laundering and the regulatory environment. They may also include a critical view of the current AML measures, questioning their effectiveness and highlighting the need for more robust and clear guidelines (Compin, 2008; Mitchell et al., 1998; Norton, 2018).

The narratives from the interviews provide further depth to this analysis, revealing real-world experiences and perceptions that either reinforce or challenge these cognitive scripts. For instance, some accountants express reservations about the effectiveness of AML measures, suggesting that their preexisting schemas include an awareness of the limitations within their role. The accountants' perception leads to a script that prioritizes professional judgment and caution over stringent adherence to protocols, especially in complex situations (Choo, 1989, 1989).

The approach of accountants to AML compliance is significantly influenced by their pre-existing schemas, which are continuously shaped and reshaped by their education, experiences, and the evolving regulatory landscape. The accountants, as rational and calculating actors, use these schemas to navigate the complexities of AML compliance (see Kroneberg, 2014; van der Steen, 2009). Understanding these cognitive scripts clarifies how accountants interpret their responsibilities, evaluate ambiguous situations, and form attitudes toward AML obligations. Their evaluative capacity, grounded in rational calculation, plays a pivotal role in how they assimilate new regulations and adapt to the dynamic and often uncertain landscape of AML compliance.

#### 6.1.2. Assimilation schemata: integrating and adapting scripts for AML compliance

The assimilation stage of the schema is where individuals integrate new information, understand typical patterns, and adapt to new AML regulations. Accountants in the professional realm of AML compliance are continually exposed to a flux of new regulations, emerging financial crimes, and evolving compliance strategies. An environment charactered by the changing landscape of financial crimes necessitates constant assimilation of information, where individuals must integrate fresh insights into their established scripts (Albarracin et al., 2021; R. Schank and Abelson, 1975; Yun and Roth, 2008). The sentiments expressed by accountants reflect this ongoing assimilation process.

The sentiments, which span a spectrum from positive to negative, highlight varying degrees of adaptation to the changing landscape of AML compliance. Accountants expressing what could be construed as positive sentiments often reveal a script that is attuned to the importance of upholding stringent compliance standards and regulatory frameworks (Choo, 1989; van der Steen, 2009). Their scripts are continuously refined as they encounter new regulatory challenges, absorb emerging industry best practices, and respond to advancements in financial monitoring technologies. The high-performance accuracy in the classification of the sentiments from the machine learning and deep learning models underscores the prevalence of this adaptive script among accountants, who are often seen as the frontline defenders against money laundering activities.

Conversely, sentiments that might be interpreted as neutral or negative suggest a different aspect of script assimilation. These sentiments often emerge from accountants grappling with the practicalities and complexities of AML compliance in real-world scenarios. They indicate scripts that are informed not only by formal training and regulatory guidelines but also by on-the-ground experiences, challenges in implementing compliance measures, and perceived inadequacies within existing AML frameworks (Amara et al., 2020; Choo, 1996; Compin, 2008). The interviews reinforce this perspective, with accountants and various gatekeepers of AML compliance voicing concerns about the effectiveness of certain AML strategies, the challenges in implementing robust compliance measures, and the real-world dilemmas they face, particularly in scenarios with potential money laundering activities.

As rational and calculating actors, accountants use their developed scripts to navigate the complexities of AML compliance. These scripts, shaped by their ability to assess and integrate new information critically, are key in guiding their responses to AML compliance challenges. The scripts appear to have not only shaped the perceptions of accountants towards AML compliance but also influenced their decision-making processes and actions in their professional roles (also see Choo, 1989, 1996; van der Steen, 2009). Understanding this assimilation process is essential for grasping the dynamics of accountants' roles in AML regulation, highlighting the diverse ways in which accountants, as rational actors, perceive and respond to AML challenges and underscoring the importance of continuous education, training, and support in helping them navigate an ever-changing regulatory landscape.

#### 6.1.3. Accommodation schemata: adjusting scripts in response to AML compliance dynamics

In the accommodation stage of schemata, accountants are engaged in a crucial process of revising and realigning their cognitive scripts based on new experiences and regulatory changes in the field of AML compliance. The accommodation stage is characterized by the adaptation and modification of existing schemata to accommodate the evolving landscape of AML practices and regulations. Evidence from the sentiments and interviews indicates a diverse range of script adjustments among accountants. These adjustments are not necessarily confined to distinct categories of positive, neutral, or negative sentiments but rather demonstrate a spectrum of adaptations to the complexities and demands of AML compliance roles.

Accountants who have shown a tendency towards what might be termed positive sentiments appear to be actively recalibrating their scripts in the accommodation stage of the schemata process. Their responses suggest an intentional integration of new information that enhances their understanding and approach to AML compliance. Such integration is reflected in their increased focus on proactive reporting and compliance, demonstrating a readiness to align their practices with the latest regulatory demands (Choo, 1996; van der Steen, 2009). As noted in the findings from the interviews and sentiment analysis, the accounting profession places a high value on regulatory adherence, continuously updating their scripts to maximize the effectiveness of their AML activities.

During the accommodation stage, the accountants exhibiting what might be perceived as neutral sentiments engage in an iterative process of script refinement. The script refinement process involves adjusting their methods and strategies to align with new information and evolving circumstances in the field of AML compliance (Butler and Gannon, 2021; R. Schank, 1980; Yun and Roth, 2008). Their approach reflects a script centered on pragmatism and the pursuit of ongoing improvement, which is essential for maintaining effectiveness and responsiveness in their professional roles (Ekblom and Gill, 2016; Kroneberg, 2014). Evidence from the interviews supports this observation, indicating that accountants with such an orientation actively seek to update and enhance their AML strategies, demonstrating a commitment to staying abreast of and adapting to emerging trends and regulatory challenges in the field.

For accountants expressing negative sentiments, the accommodation stage involves a critical reassessment of their existing scripts as rational and calculating actors. The adjustment of their perspectives and their ability to critically evaluate situations, is particularly evident when they confront the perceived challenges and limitations within AML compliance (Habib et al., 2018; Mitchell et al., 1998; Ravenda et al., 2019). Their script adaptation, therefore, reflects not just caution but also a calculated approach, especially concerning the effectiveness of measures and the complexities of self-reporting (Choo, 1989, 1996). The accommodation stage signifies their acknowledgment of the need for clearer guidelines and more comprehensive training, as well as their capacity for rational decision-making in the face of complex professional dilemmas (Ekblom and Gill, 2016; Kroneberg, 2014). The findings from the interviews support this view, revealing a script that is not only acutely aware of the boundaries and potential conflicts in AML compliance roles but also emphasizes the importance of rational and informed responses to these challenges.

## 7. Conclusion

The study examined how accountants involved in non-banking financial institutions interpret and enact their role in AML compliance, drawing on sentiment analysis of Cullen Commission testimonies and interviews with AML practitioners. The findings indicate general alignment with formal AML objectives and regulatory expectations, alongside clearly articulated constraints related to role ambiguity, limited statutory authority, fragmented guidance, and uneven enforcement. These constraints shape the performance of accountants' gatekeeping functions and help explain variation in AML implementation across NBFI sectors.

The sentiment patterns identified through machine and deep learning models reflect systematic evaluative responses rather than isolated opinions. Positive sentiment is associated with adherence to established compliance procedures, whereas negative sentiment concentrates on enforcement gaps, reliance on client disclosure, and uncertainty surrounding professional responsibility. Viewed through script theory, these patterns correspond to professional scripts embedded within prevailing institutional and regulatory arrangements rather than individual resistance to AML obligations. Taken together, the results position accountants as embedded actors within AML enforcement systems whose practices influence regulatory outcomes. Limitations in training, guidance, and professional authority may weaken AML effectiveness even where formal rules exist. Addressing these structural conditions carries implications not only for the accounting profession but also for regulators, policymakers, and scholars concerned with the design and performance of economic crime-control frameworks. The application of sentiment analysis highlights recurring evaluative patterns across testimony that illuminate institutional constraints affecting AML performance, rather than serving as a methodological contribution in its own right.

### *7.1. Limitation and direction for future researchtop of form*

The findings of this study are grounded in testimonies presented to the Cullen Commission and interviews with professionals operating within the Canadian AML context. As such, the results reflect institutional, regulatory, and professional conditions specific to British Columbia and Canada, which may limit broader generalizability. The sentiments and scripts identified may differ in jurisdictions with alternative AML regimes, enforcement capacities, or professional mandates. Future research would benefit from comparative analyses across multiple jurisdictions to assess how variations in regulatory design, professional authority, and enforcement intensity shape accountants' AML scripts and sentiment patterns.

Methodological limitations also arise from the use of machine- and deep-learning-based sentiment analysis, particularly in interpreting professional language, implicit evaluations, and contextual cues such as sarcasm. Future studies could strengthen model performance by incorporating richer contextual and socio-economic information, including institutional roles, organizational settings, and broader market conditions influencing compliance behaviour. Further advances in sentiment modeling that integrate insights from linguistics, psychology, and criminology may enhance sensitivity to complex professional discourse and strengthen the interpretive power of computational approaches in AML research.

## Declaration of Competing Interest

I acknowledge that there is no conflict-of-interest in this paper. This project was funded by the Tri-Council New Frontiers in Research Grant.

I acknowledged that I used Grammarly and EditGPT to proofread, paraphrase, and address syntax errors in this manuscript.

I have also used Azure API with Google Colab to perform Retrieval-Augmented Generation (RAG) to generate summaries of the positive and negative sentiments.

## References

Abercrombie, G., Batista-Navarro, R., 2020. Sentiment and position-taking analysis of parliamentary debates: a systematic literature review. J. Comput. Soc. Sci. 3 (1), 245–270. https://doi.org/10.1007/s42001-019-00060-w.

Alaparthi, S., Mishra, M., 2021. BERT: a sentiment analysis odyssey. J. Mark. Anal. 9 (2), 118–126. https://doi.org/10.1057/s41270-021-00109-8.

Albarracin, M., Constant, A., Friston, K.J., Ramstead, M.J.D., 2021. A variational approach to scripts. Front. Psychol. 12, 585493. https://doi.org/10.3389/fpsyg.2021.585493.

Amara, I., Khlif, H., El Ammari, A., 2020. Strength of auditing and reporting standards, corruption and money laundering: A cross-country investigation. Manag. Audit. J. 35 (9), 1243–1259. https://doi.org/10.1108/MAJ-10-2018-2026.

Atkinson, R., & Flint, J. (2001). Social research update. *Department of Sociology, University of Surrey*, 33. https://sru.soc.surrey.ac.uk/SRU33.PDF.

Becker, H., 1998. Tricks of the trade: How to think about your research while you're doing it. Chicago. University Press.

Biernacki, P., Waldorf, D., 1981. Snowball sampling: Problems and techniques of chain referral sampling. Sociol. Methods Res. 10 (2), 141–163.

Bolgorian, M., Mayeli, A., 2020. Accounting conservatism and money laundering risk. Account. Res. J. 33 (2), 343–361. https://doi.org/10.1108/ARJ-12-2018-0221.

Butler, H., Gannon, T.A., 2021. Do deliberate firesetters hold fire-related scripts and expertise? A quantitative investigation using fire service personnel as comparisons. Psychol. Crime. Law 27 (4), 383–403. https://doi.org/10.1080/1068316X.2020.1808978.

Byrne, M., O'Malley, L., Glenny, A.-M., Pretty, I., Tickle, M., 2021. Assessing the reliability of automatic sentiment analysis tools on rating the sentiment of reviews of NHS dental practices in England. PLOS ONE 16 (12), e0259797. https://doi.org/10.1371/journal.pone.0259797.

Canadian Broadcasting Corporation, 2025. CBC. Burnaby man charged in $47M money laundering scheme linked to illicit cannabis sales. 〈https://www.cbc.ca/news/canada/british-columbia/b-c-man-charged-in-47m-money-laundering-scheme-from-illegal-cannabis-1.7448311〉.

Choo, F., 1989. Cognitive scripts in auditing and accounting behavior. Account. Organ. Soc. 14 (5–6), 481–493. https://doi.org/10.1016/0361-3682(89)90013-5.

Choo, F., 1996. Auditors' knowledge content and judgment performance: A cognitive script approach. Account. Organ. Soc. 21 (4), 339–359. https://doi.org/10.1016/0361-3682(95)00048-8.

Choo, F., Tan, K., 2007. An "American Dream" theory of corporate executive Fraud. Account. Forum 31 (2), 203–215. https://doi.org/10.1016/j.accfor.2006.12.004.

Compin, F., 2008. The role of accounting in money laundering and money dirtying. Crit. Perspect. Account. 19 (5), 591–602. https://doi.org/10.1016/j.cpa.2007.01.001.

Cullen, A., 2022a. Commission of Inquiry into Money Laundering in British Columbia. Government of British Columbia. 〈https://cullencommission.ca/files/reports/CullenCommission-FinalReport-Full.pdf〉.

Cullen, A., 2022b. Commission of Inquiry into Money Laundering in British Columbia (Cullen Report): Final Report, Commission of Inquiry into Money Laundering in British Columbia. Government of British Columbia. 〈https://policycommons.net/artifacts/2470962/cullencommission-finalreport-full/3492968/〉. on 10 Feb 2023. CID: 20.500.12592/bd79vf.

Davidescu, A.A., Lobont, O.R., Manta, E.M., Hapau, R.G., 2023. Mapping the Field. A Text Analysis of Money Laundering Research Publications. In: Tyagi, In.P., Grima, S., Sood, K., Balamurugan, B., Özen, E., Eleftherios, T. (Eds.), Contemporary Studies in Economic and Financial Analysis. Emerald Publishing Limited, pp. 171–187. https://doi.org/10.1108/S1569-37592023000110B011.

Davis, J.S., Pesch, H.L., 2013. Fraud dynamics and controls in organizations. Account. Organ. Soc. 38 (6–7), 469–483. https://doi.org/10.1016/j.aos.2012.07.005.

de Koker, L., Malala, J., Azinge-Egbiri, N., Adeyemo, F., Nwabuzor, C., Otudor, L., 2025. Financial and Economic Crimes Across Disciplines: Perspectives from the Global South. J. Econ. Criminol., 100201 https://doi.org/10.1016/j.jeconc.2025.100201.

Dellaportas, S., 2013. Conversations with inmate accountants: Motivation, opportunity and the fraud triangle. Account. Forum 37 (1), 29–39. https://doi.org/10.1016/j.accfor.2012.09.003.

Donegan, J.J., Ganon, M.W., 2008. Strain, Differential Association, and Coercion: Insights from the Criminology Literature on Causes of Accountant's Misconduct. Account. Public Interest 8 (1), 1–20. https://doi.org/10.2308/api.2008.8.1.1.

Edwards, C., Edwards, A., Spence, P.R., Westerman, D., 2016. Initial Interaction Expectations with Robots: Testing the Human-To-Human Interaction Script. Commun. Stud. 67 (2), 227–238. https://doi.org/10.1080/10510974.2015.1121899.

Ekblom, P., Gill, M., 2016. Rewriting the Script: Cross-Disciplinary Exploration and Conceptual Consolidation of the Procedural Analysis of Crime. Eur. J. Crim. Policy Res. 22 (2), 319–339. https://doi.org/10.1007/s10610-015-9291-9.

Gabbioneta, C., Greenwood, R., Mazzola, P., Minoja, M., 2013. The influence of the institutional context on corporate illegality. Account. Organ. Soc. 38 (6–7), 484–504. https://doi.org/10.1016/j.aos.2012.09.002.

German, P., 2019. Dirty Money—Part 2: Turning the Tide—An Independent Review of Money Laundering in B.C. Real Estate, Luxury Vehicle Sales & Horse Racing, Commission of Inquiry into Money Laundering in British Columbia. Government of British Columbia. ⟨https://policycommons.net/artifacts/2470967/dirty_money_report_part_2/3492973/⟩. on 10 Feb 2023. CID: 20.500.12592/ppr5t5.

Ghiassi, M., Lee, S., 2018. A domain transferable lexicon set for Twitter sentiment analysis using a supervised machine learning approach. Expert Syst. Appl. 106, 197–216. https://doi.org/10.1016/j.eswa.2018.04.006.

Gilbert, J., 2024. Scripting mortgage fraud for the motion picture: "Fraud and its interrelationship with the financial services sector in the UK. J. Econ. Criminol. 5, 100084. https://doi.org/10.1016/j.jeconc.2024.100084.

Guest, G., Bunce, A., Johnson, L., 2006. How Many Interviews Are Enough?: An Experiment with Data Saturation and Variability. Field Methods 18 (1), 59–82. https://doi.org/10.1177/1525822X05279903.

Guest, G., Namey, E., Chen, M., 2020. A simple method to assess and report thematic saturation in qualitative research. PLOS ONE 15 (5), e0232076. https://doi.org/10.1371/journal.pone.0232076.

Habib, A., Costa, M.D., Huang, H.J., Bhuiyan, Md.B.U., Sun, L., 2020. Determinants and consequences of financial distress: review of the empirical literature. Account. Financ. 60 (S1), 1023–1075. https://doi.org/10.1111/acfi.12400.

Habib, A., Hasan, M.M., Al-Hadi, A., 2018. Money laundering and audit fees. Account. Bus. Res. 48 (4), 427–459. https://doi.org/10.1080/00014788.2017.1392842.

Han, J., Huang, Y., Liu, S., Towey, K., 2020. Artificial intelligence for anti-money laundering: a review and extension. Digit. Financ. 2 (3–4), 211–239. https://doi.org/10.1007/s42521-020-00023-1.

Havrlant, L., Kreinovich, V., 2017. A simple probabilistic explanation of term frequency-inverse document frequency (tf-idf) heuristic (and variations motivated by this explanation). Int. J. Gen. Syst. 46 (1), 27–36. https://doi.org/10.1080/03081079.2017.1291635.

Kennedy, A., Inkpen, D., 2006. Sentiment classification of movie reviews using contextual valence shifters. Comput. Intell. 22 (2), 110–125. https://doi.org/10.1111/j.1467-8640.2006.00277.x.

Kroneberg, C., 2014. Frames, scripts, and variable rationality: An integrative theory of action. In: Manzo, In.G. (Ed.), Analytical Sociology, 1st ed. Wiley, pp. 95–123. https://doi.org/10.1002/9781118762707.ch04.

Kumar, V., Subba, B., 2020. A TfidfVectorizer and SVM based sentiment analysis framework for text data corpus. Natl. Conf. Commun. (NCC) 2020, 1–6. https://doi.org/10.1109/NCC48643.2020.9056085.

Kute, D.V., Pradhan, B., Shukla, N., Alamri, A., 2021. Deep learning and explainable artificial intelligence techniques applied for detecting money laundering–a critical review. IEEE Access 9, 82300–82317. https://doi.org/10.1109/ACCESS.2021.3086230.

Lawrence, S., Low, M., Sharma, U., 2010. Prem Sikka and the media: Using the media to hold accountants to account. Qual. Res. Account. Manag. 7 (3), 249–269. https://doi.org/10.1108/11766091011072747.

Lehman, C.R., Okcabol, F., 2005. Accounting for crime. Crit. Perspect. Account. 16 (5), 613–639. https://doi.org/10.1016/j.cpa.2003.08.003.

Liao, S., Wang, J., Yu, R., Sato, K., Cheng, Z., 2017. CNN for situations understanding based on sentiment analysis of twitter data. Procedia Comput. Sci. 111, 376–381. https://doi.org/10.1016/j.procs.2017.06.037.

Lindén, K., Jauhiainen, T., Hardwick, S., 2023. FinnSentiment: A Finnish social media corpus for sentiment polarity annotation. Lang. Resour. Eval. 57 (2), 581–609. https://doi.org/10.1007/s10579-023-09644-5.

Löhlein, L., Huber, C., 2024. The end of audit. Spectacle and love in the audit society. Qual. Res. Account. Manag. 21 (1), 65–76. https://doi.org/10.1108/QRAM-11-2021-0199.

Lokanan, M., 2018. Theorizing Financial Crimes as Moral Actions. Eur. Account. Rev. 27 (5), 901–938. https://doi.org/10.1080/09638180.2017.1417144.

Lokanan, M., 2023. Analyzing public sentiments on the Cullen Commission inquiry into money laundering: Harnessing deep learning in the AI of Things Era. Front. Internet Things 2, 1287832. https://doi.org/10.3389/friot.2023.1287832.

Lokanan, M.E., 2023. The tinder swindler: Analyzing public sentiments of romance fraud using machine learning and artificial intelligence. J. Econ. Criminol. 2, 100023. https://doi.org/10.1016/j.jeconc.2023.100023.

Maloney, M., Simerville, T., Unger, B., 2019. Combatting Money Laundering in BC Real Estate. B. C. Gov. ⟨http://brigitteunger.nl/wp-content/uploads/2019/06/6792_Combatting_MoneyLaundering_Report_FINAL.pdf⟩.

Martini, M., 2017. Transparency International. Doors wide Open. Corrupt. Real. Estate four key Mark. ⟨https://www.transparency.org/whatwedo/publication/doors_wide_open_corruption_and_real_estate_in_four_key_markets⟩.

Mitchell, A., Sikka, P., Willmott, H., 1998. Sweeping it under the carpet: The role of accountancy firms in moneylaundering. Account. Organ. Soc. 23 (5–6), 589–607. https://doi.org/10.1016/S0361-3682(98)00010-5.

Morales, J., Gendron, Y., Guénin-Paracini, H., 2014. The construction of the risky individual and vigilant organization: A genealogy of the fraud triangle. Account. Organ. Soc. 39 (3), 170–194. https://doi.org/10.1016/j.aos.2014.01.006.

Murphy, P.R., 2012. Attitude, Machiavellianism and the rationalization of misreporting. Account. Organ. Soc. 37 (4), 242–259. https://doi.org/10.1016/j.aos.2012.04.002.

Norton, S.D., 2018. Suspicion of money laundering reporting obligations: Auditor compliance, or sceptical failure to engage? Crit. Perspect. Account. 50, 56–66. https://doi.org/10.1016/j.cpa.2017.09.003.

Oliveira, N., Cortez, P., Areal, N., 2014. Automatic creation of stock market lexicons for sentiment analysis using StockTwits data. Proc. 18th Int. Database Eng. Appl. Symp. IDEAS 115–123. https://doi.org/10.1145/2628194.2628235.

Pang, B., Lee, L., 2004. A Sentim. Educ. Sentim. Anal. Using Subj. Summ. Based Minim. Cuts. https://doi.org/10.48550/ARXIV.CS/0409058.

Power, M., 2013. The apparatus of fraud risk. Account. Organ. Soc. 38 (6–7), 525–543. https://doi.org/10.1016/j.aos.2012.07.004.

Ravenda, D., Valencia-Silva, M.M., Argiles-Bosch, J.M., García-Blandón, J., 2019. Money laundering through the strategic management of accounting transactions. Crit. Perspect. Account. 60, 65–85. https://doi.org/10.1016/j.cpa.2018.08.003.

Sathye, M., 2024. Defiance as an image restoration strategy: Refining the reputation risk management framework. Qual. Res. Account. Manag. 21 (5), 494–523. https://doi.org/10.1108/QRAM-12-2023-0249.

Schank, R., 1980. Language and memory. Cogn. Sci. 4 (3), 243–284. https://doi.org/10.1016/S0364-0213(80)80004-8.

Schank, R., Abelson, R., 1975. Scr. plans Knowl. 75, 151–157.

Schank, R.C., Abelson, R.P., 2013. Scripts, Plans, Goals, and Understanding, 0 ed.). Psychology Press. https://doi.org/10.4324/9780203781036.

Sikka, P., Willmott, H., 1998. Accounting for the public interest: Money, arms and tax. Am. Account. Assoc. Public Interest 26 (2), 8.

Smith, A.M., Walsh, J.R., Long, J., Davis, C.B., Henstock, P., Hodge, M.R., Maciejewski, M., Mu, X.J., Ra, S., Zhao, S., Ziemek, D., Fisher, C.K., 2020. Standard machine learning approaches outperform deep representation learning on phenotype prediction from transcriptomics data. BMC Bioinforma. 21 (1), 119. https://doi.org/10.1186/s12859-020-3427-8.

Summers, G., Tudor, K., 2000. Cocreative transactional analysis. Trans. Anal. J. 30 (1), 23–40. https://doi.org/10.1177/036215370003000104.

Todd, D., 2024. Canadian governments fail to stop money laundering because they want the cash, says law prof. Vanc. Sun. ⟨https://vancouversun.com/opinion/columnists/canadian-governments-money-laundering-cash-law-prof⟩.

Tomlinson, K., 2018. Globe investigation into money laundering in B.C. real estate will lead to new rules, AG says. Globe Mail. ⟨https://www.theglobeandmail.com/news/national/globe-investigation-into-money-laundering-in-bc-real-estate-will-lead-to-new-rules-ag-says/article38018921/⟩.

Tomlinson, K., & Xiao, X. (2018). B.C. vows crackdown after Globe investigation reveals money-laundering scheme. *The Globe and Mail*. ⟨https://www.theglobeandmail.com/news/investigations/real-estate-money-laundering-and-drugs/article38004840/?utm_medium=Referrer%3A+Social+Network+%2F+Media&utm_campaign=Shared+Web+Article+Links⟩.

Unerman, J., Chapman, C., 2014. Academic contributions to enhancing accounting for sustainable development. Account. Organ. Soc. 39 (6), 385–394. https://doi.org/10.1016/j.aos.2014.07.003.

van der Steen, M., 2009. Inertia and management accounting change: The role of ambiguity and contradiction between formal rules and routines. Account. Audit. Account. J. 22 (5), 736–761. https://doi.org/10.1108/09513570910966351.

Vathsala, M.K., Holi, G., 2020. RNN based machine translation and transliteration for Twitter data. Int. J. Speech Technol. 23 (3), 499–504. https://doi.org/10.1007/s10772-020-09724-9.

Yun, M., Roth, M., 2008. Terrorist Hostage-Taking and Kidnapping: Using Script Theory to Predict the Fate of a Hostage. Stud. Confl. Terror. 31 (8), 736–748. https://doi.org/10.1080/10576100802206566.

Zhang, H., Gan, W., Jiang, B., 2014. Machine Learning and Lexicon Based Methods for Sentiment Classification: A Survey. 11th Web Inf. Syst. Appl. Conf. 2014, 262–265. https://doi.org/10.1109/WISA.2014.55.

Zhang, W., Gao, F., 2011. An improvement to naive bayes for text classification. Procedia Eng. 15, 2160–2164. https://doi.org/10.1016/j.proeng.2011.08.404.

Zhang, Y., Jin, R., Zhou, Z.-H., 2010. Understanding bag-of-words model: A statistical framework. Int. J. Mach. Learn. Cybern. 1 (1–4), 43–52. https://doi.org/10.1007/s13042-010-0001-0.

Zhao, R., Mao, K., 2018. Fuzzy bag-of-words model for document representation. IEEE Trans. Fuzzy Syst. 26 (2), 794–804. https://doi.org/10.1109/tfuzz.2017.2690222.


**Mark Lokanan** is a Professor in the Faculty of Management at Royal Roads University. He is a graduate from the School of Criminology, Simon Fraser University, Canada and is an expert in machine learning, AI, fraud, forensic and investigative accounting.