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A conceptual decision support system framework for applying detective analytics

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Abstract

The implementation of detective analytics continues to be challenging for many organisations. The challenges could be attributed to a lack of a decision support system (DSS) framework for applying detective analytics. Thus, this study was conducted following the qualitative method in which existing materials (literature) were gathered covering a wide spectrum. Translation of actor-network theory (ANT) was applied as a lens for the data analysis. The findings reveal three primary critical factors affecting the implementation of detective analytics: a lack of understanding of the interrelationships between various actors, inconsistent application of analytical methods, and the selection of inappropriate decision techniques. Based on these factors, a conceptual DSS framework is proposed. The conceptual DSS framework aims to address these issues by offering a more structured approach to integrating detective analytics into decision-making processes. The DSS framework has implications for both technology and business personnel. The paper contributes to the growing body of knowledge on improving the application of detective analytics in organisations.

Keywords: actor-network theory, artificial intelligence, detective analytics, decision support system, decision support framework

Introduction

Artificial Intelligence (AI) is the digital simulation of human intelligence processes using machine language for problem-solving and decision-making (El Samad, Nasserddine, & Kheir, 2023). The tasks include predefined rules and algorithms for learning, problem-solving, language understanding, and decision-making (Mathew, Brintha & Jappes, 2023). The scope of AI is increasingly broadened, constituting many more solutions. In some quarters, detective analytics is categorised among AI tools (Vanani & Shaabani, 2021). Charles et al. (2023) suggest reasons for including detective analytics as an AI tool. Detective analytics is the latest of the analytics family that includes descriptive, diagnostic, predictive, and prescriptive. Detective analytics focuses on automation and algorithms using various types of data and techniques, towards solutions and recommendations (Empl & Pernul, 2023).

Since its emergence, there has been an overwhelming interest across sectors (Mlambo & Iyamu, 2024). These include manufacturing, finance, health, energy, technology, retail, transportation and logistics (Rasjid, 2021; Menezes et al., 2019). The increasing interest is congruent with detective analytics for organisations, such as the instant discovery of anomalies at various levels (Getachew, Beshah & Mulugeta, 2024). Mlambo and Iyamu (2024) revealed that, despite the growing popularity of detective analytics, many organisations, particularly financial institutions, are challenged with the implementation. The authors further attributed the challenges to a lack of guidelines.

Detective analytics enables the analysis of historical data, the detection of anomalies and the identification of potential issues (Kaushik & Dahiya, 2022). According to Weller et al. (2023), the use of detective analytics assists in making better and more informed decisions in an organisation. If properly implemented or integrated with other solutions, detective analytics increases the accuracy level in revealing hidden problems and anomalies in an organisation, such as inconsistencies, fraud or just inefficiencies that can go unnoticed (Islam et al., 2021). Additionally, Darwish (2024) argues that scaling detective analytics improves organisational performance but can be challenging. Some challenges include interrelationships, inconsistent application of methods and techniques, and selecting inappropriate decision techniques. Hence, it is important to employ a decision support system (DSS) framework to help address the challenges and limit risk.

A DSS is an approach used by organisations, to manage and assist decision-making (Wang, Setiawansyah & Rahmanto, 2024). Nasar et al. (2023) suggest that DSS helps to analyse data and present valuable and relevant information that is then used to make informed decisions. The DSS approach has been used to enable and support the implementation of many systems across sectors (Craja, Kim & Lessmann, 2020; Musen, Middleton, & Greenes, 2021; Shim et al., 2002; Zhai et al., 2020). Primarily, this is because a DSS can assist in the decision-making process, harnessing upcoming technology solutions. For example, machine learning algorithms and advanced data analytics tools can be integrated into a DSS to maintain comprehensive autonomy and enact consistency. Thus, the approach can also be employed to guide the implementation and use of detective analytics to improve its efficiency and effectiveness.

The critical and essential need for detective analytics is the motivation for embarking on this study. It spans the objective, which is to propose a conceptual decision support system framework for applying detective analytics in organisations. The proposed framework is intended to integrate detective analytics into a decision-making process in an organisation. Potentially, this will fortify the implementation and use of detective analytics and enhance its functions to a high degree of efficiency and effectiveness.

Problematising applying detective analytics

Despite the advancement and significance of detective analytics, many organisations struggle with its implementation. Primarily, this is attributed to factors such as a lack of understanding of interrelationships, inconsistent application of methods and techniques, and selecting inappropriate decision techniques. This leads to the problematisation of this study’s topic, as presented in Table 1.

Leading to the challenges, firstly, the influencing factors are empirically known. Secondly, the challenges are increasing because it is unclear how the factors manifest themselves in the process of implementing detective analytics in organisations. Consequently, organisations are confused about the implementation of the tools. As a result, some organisations are experiencing impediments, which affect the benefits of implementing detective analytics to mitigate financial crimes and anomalies in transactions.

Table 1. Problematisation

Problem	Implications and consequences
Interrelationships	The links between sets of data are hardly understood using detective analytics. This makes it difficult to follow the actors and endorse strategies for mitigating irregular activities in an environment. Consequently, data quality is compromised (Fan & Geerts, 2022). When this happens, it becomes impossible or prohibitive to achieve the organisational goals.
Inconsistent	Inconsistent methods may lead to confusion or uncertainty about the quality of the analysis, delays in issuing warnings and preventive actions (Muhsen et al., 2023). This allows internal personnel to manipulate the processing of data for personal interest. Also, inconsistency makes it easier for intruders.
Inappropriate decision techniques	Inappropriate decision techniques may lead to inaccurate or unreliable predictions, hindering the ability to act proactively and prevent negative outcomes (Jinad et al., 2024). Selecting inappropriate decision techniques in detective analytics can undermine the effectiveness, reliability, and fairness of the decision support system (Marabelli, Newell & Handunge, 2021).

Literature review

The interest and popularity of detective analytics are growing briskly. This could be associated with various factors. Mlambo and Iyamu (2024) attribute the increasing interest in detective analytics to its strength, to creatively and innovatively produce detailed insights. Empl and Pernul (2023) suggest that the strength of detective analytics lies in the ability to operationalise data from various sources. The strength and premise, therefore, entail the interrelationship of the actors involved in an operation. However, the interrelationship is often not understood because of the unprecedented number or complexity of the interconnecting links (Rasjid, 2021). This affects the accuracy of identifying underlying challenges in a transaction or operation. Menezes et al. (2019) argued that detective analytics determines the level of precision in an activity or transaction; therefore, compromise should be avoided, circumstantially. As a result of the unknown, detective analytics are deployed inconsistently, from one individual or organisation to another.

Owing to the sensitivity and delicacies associated with applying detective analytics, consistency is vital. In examining complex data using analytical methods and techniques, consistency becomes even more important (Oatley et al., 2020). Inconsistent application affects the effectiveness and efficiency of an investigation. Spann (2013) suggests that some of the consequences of applying detective analytics inconsistently include bias and inadequacy, incorrectness of results, and a lack of standard operating procedure. DSS has been used to provide guidelines that are congruent with set processes and workflow in many circumstances (Liu et al., 2010). DSS predefines and standardises methodologies that can be used for data analytics, to ensure consistency and reduce biases across cases (Soori et al., 2024). Additionally, DSS integrates data from disparate sources and different methods into one platform (March & Hevner, 2007).

Appropriateness is key to the usefulness of detective analytics by organisations. On the one hand, detective analytics diagnoses collected data to eliminate and rectify inappropriate values used by organisations (Menezes et al., 2019). On the other hand, detective analytics is applied to data to improve the accuracy of detecting intrusion and mitigating irregular activities (Rasjid, 2021). However, the operations can be hampered if an inappropriate procedure is employed. Mlambo and Iyamu (2024) suggest that although detective analytics can be used to trace, track, and prevent financial crime in an organisation, it requires an appropriate mechanism. Getachew et al. (2024) explained that the use of detective analytics can be improved through appropriateness by providing more up-to-date information.

Interrelationships, inconsistent application of methods and techniques, and selection of inappropriate decision techniques happen at different moments using detective analytics. In each moment, translation is required within context. In actor-network theory (ANT), translation is conceptualised as a complex process of negotiation; in the process, meanings and interests shift and gain ground (Iyamu, 2024; Waeraas & Nielsen, 2016). Therefore, through translations, detective analytics can highlight how decisions, actions, and data flow through a network (Mlambo & Iyamu, 2024). This can uncover previously hidden dependencies and interrelationships that affect outcomes, making it easier to understand why certain events or anomalies occur (Garcia-Teodoro et al., 2009). Sarker, Sarker and Sidorova (2006) argue that through the lens of ANT, inconsistencies in processes or activities can be traced and rectified. This is important in employing translation for analysis towards developing a DSS, for detective analytics. Detective analytics aims to uncover inconsistencies and identify where processes might be misaligned or inappropriate for achieving the desired outcome (Menezes et al., 2019).

Underpinning theory: Actor-network theory

Actor-network theory (ANT) is a sociotechnical theory that focuses on actors' relationships and the translation of entities, including how negotiations shift at various moments (Latour, 1992; Callon, 1986). In ANT, "translation" is the process through which actors negotiate their roles and influence each other to form a stable network (Lezaun, 2017). According to Law (1992: 386), "translation implies transformation and the possibility of equivalence, the possibility that one thing (for example, an actor) may stand for another (for instance, a network)". This allows an acceptable, among actors, translation of processes, activities, and events, to enable a better understanding of interrelationships, and appropriateness of techniques, and eradicate or reduce inconsistency.

Translation is one of the central concepts of ANT. The concept of translation involves actors shifting negotiation and aligning various interests to form a collective and durable alliance. Diaz Andrade and Urquhart (2010) suggest that the concept guides the reconstruction of a complex network of actors. ANT's view of translation is not just about linguistics, but as a transformative process that creates networks and allows them to function as a unified whole (Callon, 1986). The transformative practice focuses on reconnections, re-assemblages, or re-associations. Exemplarily, Birke and Knierim (2020) showed how the translation concept guides various categories of transformation, including the interpretation of the results.

Since the intention was to develop an argument on how certain factors influence the implementation of detective analytics, contextual analysis was most appropriate. Walsham (1997) explains that a contextual analysis is important because it enables the capturing of the strength and flexibility of actors' interests and their power to influence. Gao (2005) describes the power to influence as the translation of capability to attract interests. The process entails following the actors within the gathered literature, where an actor translates the objectives and other actors that could align are identified (Callon, 1986).

Methodological approach

This research is grounded in qualitative methods, which seek to understand the deeper meanings, patterns, and complexities of phenomena (Minichiello et al., 2010). Acknowledging two philosophical perspectives, which are ontology and epistemology (Al-Ababneh, 2020). Ontologically, both detective analytics and DSS exist, and there are multiple realities. Moreover, the existence of both detective analytics and DSS is well-established, how a DSS can be leveraged for detective analytics remains unexplored and unknown. What is not known is how a DSS can be used as a guide to applying detective analytics in organisations.

Data collection
The document analysis technique was used to gather existing literature (materials). The technique was deemed most appropriate for two reasons. Firstly, the technique enables the broadening of sources and varieties of the literature. This allows for the systematic rationalisation of a diverse range of sources, including books and peer-reviewed articles (Taherdoost, 2021). Secondly, document analysis facilitates the identification and extraction of relevant data, focusing on the core areas of the study. This helps to streamline the focus on detective analytics, decision support systems, decision support frameworks, and actor-network theory (ANT), which are central to the study.

A set of criteria, which includes publication year range and credible source, was applied in gathering the literature towards achieving the study's objective, which was to propose a conceptual decision support system framework for applying detective analytics in organisations. Based on the criteria, only the literature published within the last ten years (2014–2024) was gathered. The significance was to avoid the debate or argumentation that has become obsolete in the academic and public discourse. The timeframe range is crucial to gaining insights into the evolution of the concepts and their associated meanings over time (Iyamu, Nehemia-Maletzky & Shaanika, 2016). The literature was collected from academic databases such as EBSCOhost, AIS, IEEE, and Emerald. These sources were used because they were deemed credible and reliable, ensuring the quality of the materials (Nyikana & Iyamu, 2023).

Initially, sixty articles were gathered. This could be attributed to the newness of the topic. Detective analytics is an emerging subject. Academic articles focusing on detective analytics are hard to find. After a review of the articles, only thirty-seven fulfilled the criteria set for the data collection. This approach ensured that the data collected was both relevant to the study's core themes and drawn from credible and up-to-date sources.

Data analysis
Guided by the theoretical framework (ANT), the interpretive approach was applied for the analysis of the data because it seeks to explore the meanings, social dynamics, and interactions embedded within existing documents (Lim, 2024). The analysis focused on how actors' (human and non-human) interests, interactions through negotiation, and their capacities to act influenced the development and operation relating to detective analytics. ANT's concept of translation helped to reveal the criticality of interrelationships and inconsistency from interaction between actors.

In trying to gain an understanding of how using detective analytics can be inscribed into human actors, we identify inconsistencies in patterns, and inappropriate approaches were employed in some quarters, which causes resistance. Also, we found that the data affirmed that policy and stringent regulations, which can be described as irreversibility in ANT, can help buy-in and implement detective analytics.

The study seeks to reveal the complexities of interests, negotiations, and alignments that shape the effectiveness of applying and supporting detective analytics in organisations. We revealed and affirmed that interrelationship, inconsistency and inappropriateness are the primary factors influencing the use of detective analytics. Using the subjective approach, we further examine the factors to gain a deeper understanding of how they influence the implementation of detective analytics. First, we established what each factor constitutes. This helps to understand and develop a conceptual DSS framework that can be used to enable detective analytics secondly we idendigied the transformation of the factors of Iinterrelationship, Inconcsistnecy, and Inappropirateness. They are descibeed in the following sections.

Interrelationship
In the implementation of detective analytics, interrelationship entails the connection and correlation of actors, whether humans or non-humans. However, in the process, disconnection happens between actors. According to Turkay, Laramee & Holzinger (2017), the disjoint nature of elements highlights the challenge of connecting separate data sources, but overcoming this disconnection is crucial for creating a cohesive and integrated system that enables meaningful interactions across tools, data, and actors. The lack of interconnectedness between components affects the development or use of a DSS to support or enable detective analytics.

The significance of data correlation lies in its ability to align and integrate various data sources, ensuring a seamless flow of information that fosters coherent analysis and supports informed decision-making (Biswas et al., 2021). Aligning or connecting disjoint elements into a coherent network, ensuring meaningful interaction between data sources, tools, and actors (Kassen, 2020).

Inconsistency
Inconsistency manifests in a lack of standardisation and data conflict during the detective analytics implementation. Wen et al. (2024) argued that standardisation harmonises data processing methods, reducing inconsistencies and enabling smooth integration, which enhances the reliability and accuracy of the data analysis. In contrast, the implementation of detective analytics is persistently encountering inconsistent processes (Mlambo & Iyamu, 2024). This seems to be emanating from decision-making.

Conflicting data results from inconsistencies in tools and methods being used to either collect, process or analyse data. The challenge is that detective analytics relies on the data (Menezes et al., 2019). There is a need for effective reconciliation and standardisation, as unresolved discrepancies can undermine the integrity of the analysis and hinder meaningful insights. Achieving uniformity and harmony in data processing and methods through alignment, reducing discrepancies and ensuring data integration (Davis et al., 2020).

Inappropriateness
Rationality and unreliability are some critical attributes of inappropriateness in the implementation of detective analytics. Rationality affects how tools, methods, and data are logically aligned and contextually appropriate. Consequently, the reliability of data using the detective analytics becomes questionable or even invalid and irrelevant. The use of logical and relevant tools and methods will result in an alignment between organisational goals and decisions that are made within the organisation (Cheng et al., 2021), making the tools essential for a DSS.

One of the criticalities of the detective analytics lies in its reliability. However, it can be unreliable. Nivedhaa (2024) alludes that unreliability can compromise the validity of the data analysis, leading to inaccurate conclusions and undermining the trustworthiness. This ultimately depicts the whole purpose of the DSS, which is to aid the decision-making process. Ensuring tools, data, and methods are rational and contextually appropriate, continuously adapting to the specific needs of the investigation to maintain reliability (Hao, Demir & Eyers, 2024).

A Conceptual Decision Support System Framework For Detective Analytics

In the second section, the critical factors challenging detective analytics were problematized and their consequences were discussed. The factors include a lack of understanding of interrelationships, inconsistent application of methods and techniques, and selecting inappropriate decision techniques. Through the lens of ANT, the factors were examined as presented in the section above. Based on the above section, a conceptual decision support system (DSS) framework (Figure 1) for applying detective analytics in organisations was developed. Using ANT, key themes emerged from how the factors transform (manifest) themselves in influencing detective analytics. This makes the factors critical for a DSS and offers insights when applying detective analytics.

The discussion that follows the framework (Figure 1) links the perspectives of the influencing factors with existing literature. It also highlights the practical significance of these factors.

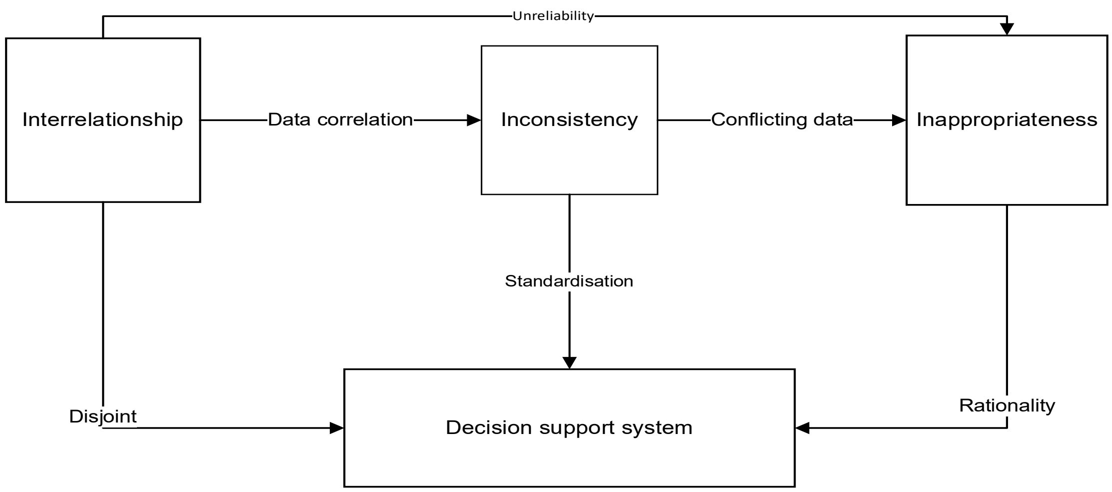

Figure 1. A conceptual decision support system framework for applying detective analytics

Interrelationship

Interrelationship is the connection and interaction between elements of a system. In the case of a DSS for detective analytics, interrelationship poses a problem when the roles, responsibilities, and interactions between actors are not clearly defined or aligned. In this context, actors could include data sources, analytic tools, fraud investigators, and external stakeholders. This causes fragmentation or disconnection in the decision-making process (Craps & Brugnach, 2015). Fragmentation impedes the system's ability to function effectively, generating insights that are actionable and leading to making consistent and informed decisions. The absence of coordination and interconnection between elements such as data sources, tools, or actors creates a risk of disjoint leading to fragmented or isolated pieces of information that are not easily connected or actionable (Carreño, 2024). Ideally, these elements should seamlessly interconnect and function together. Each element may function independently, but without proper alignment, the data or tools cannot be used effectively in conjunction with one another.

A DSS should transform raw data collected from disparate sources into actionable insights (Qadeer & Davis, 2023). The misalignment of elements hinders the flow of information, which potentially results in inefficiencies in how the DSS works. To ensure the effectiveness of the DSS, alignment and integration of the elements involved are essential. Towards enhancing the DSS, there is a need to address the disjointedness by enabling the actors to communicate and integrate smoothly, ensuring the involved analytical tools are interoperable and that they can function in unison. When these elements are appropriately aligned, the DSS's capacity will increase, and it will offer more thorough, precise, and useful insights that help with decision-making within an organisation.

Inconsistent

Detective analytics can interpret data in multiple ways, depending on the tools, algorithms, or analytical methods employed by different stakeholders (Oatley, 2022). Hargrave and Van de Ven (2017) argue that the inconsistency problem arises when different actors interpret data in contradictory ways, leading to confusion or conflicting insights that undermine the decision-making process. This leads to conflicting data, which occurs when different elements of the DSS use inconsistent formats or approaches, and conflicting interpretations of the same data can occur, undermining the reliability of the insights generated (Kovari, 2024). As a result, the DSS cannot reliably provide recommendations useful for accurate decision-making. If standardisation can be achieved wholistically, inconsistencies will be managed and the DSS can be reliable and effective. However, the use of standardisation can create uniformity.

Standardisation is the process of ensuring consistency in data formats, analytical methodologies and decision-making protocols (Szukits & Móricz, 2024). Standardisation ensures that data inputs align, and consistency is maintained in processing, analysis and interpretation of data (Leiva & Castro, 2025). According to Aldoseri, Al-Khalifa and Hamouda (2023), when standardisation is lacking, inconsistencies arise, leading to conflicting interpretations of data. Translation helps identify where inconsistencies arise, whether due to different methods of data collection, processing, or analysis, and it facilitates the development of standardised protocols and shared frameworks to ensure uniformity across the network (Sekgweleo & Iyamu, 2022). This will help create an integrated system in which all elements work together towards a goal and, in the process, enhance reliability, consistency, and accuracy in insights.

Inappropriate decision techniques

The inappropriateness of decision techniques problem occurs when data, analysis or decision-support recommendations are not relevant or suitable for the context in which they are applied. The effectiveness of the tools used is compromised as much as that of the output, which can be irrelevant, misleading, and unsuitable. This leads to compromised logical thinking or rationality in the decision-making process. Rationality refers to the logic, coherence, and suitability of methods or tools for solving a particular problem (Nishant, Schneckenberg & Ravishankar, 2024). It ensures that the goals of the organisations align with the system outputs, recommendations, and decisions because the tools and methods chosen and used are logical and suitable. Dung (2023) alludes that if the data or tools are irrational or misaligned with the needs of an organisation, the system's outputs may be inappropriate. If these elements are unreliable and not appropriate for the context of a specific decision-making process, they may provide misleading or irrelevant outputs.

Conclusion

The study reveals factors which influence the implementation of detective analytics. Based on the factors, we propose a conceptual decision support system framework for detective analytics that offers a structured approach to overcoming associated challenges in organisations. By utilising ANT translation and qualitative methods, this study highlights critical issues such as the lack of understanding of interrelationships, inconsistent application of methods, and the selection of inappropriate decision techniques. The framework provides a pathway to address these gaps, promoting a more coherent and effective integration of detective analytics into decision-making processes.

The study contributes to improving the practical application of detective analytics, enabling organisations to make more informed, data-driven decisions and enhancing overall operational effectiveness. Even though the objective of the study was successfully achieved, there is room for enhancement. Future research could further refine the framework through empirical testing and explore its adaptability across different organisational contexts.

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