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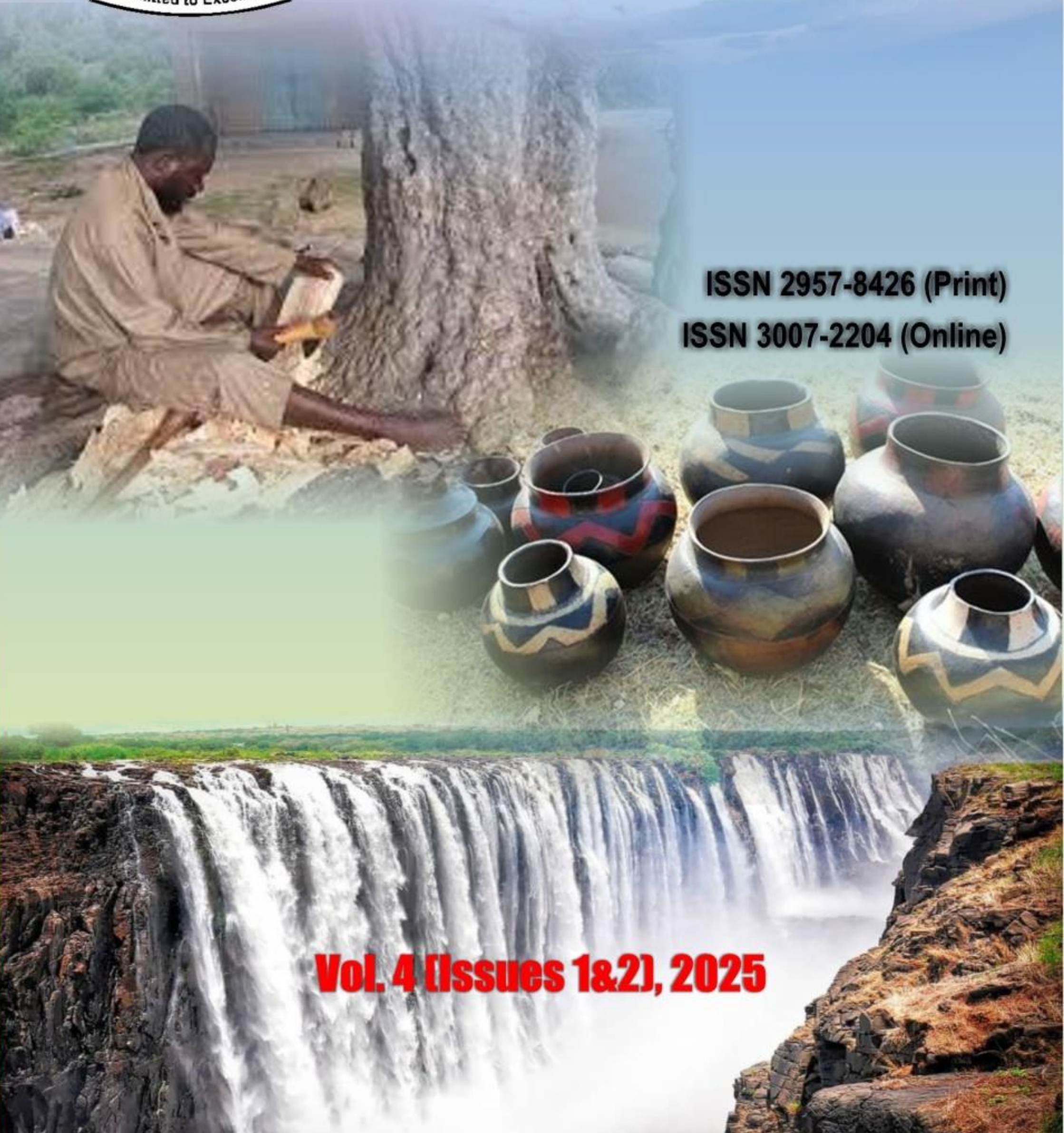
JOURNAL OF DESIGN, INNOVATIVE THINKING AND PRACTICE



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Planners, engineers, social scientists, business experts, scholars and practitioners from various fields.

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Using the Technology Acceptance Model in Assessing the Impact of Financial Intelligence Systems on Money Laundering Detection in Zimbabwean Financial Institutions

JIMU TAFADZWA[1] AND LEDWIN CHIMWAI[2]

Abstract

Money laundering posed significant global threats, prompting urgent reforms and technological advancements. In this context, a study was conducted to investigate the acceptance of financial intelligence systems (FIS) among employees in Zimbabwean financial institutions. Utilising a quantitative, cross-sectional survey design based on the Technology Acceptance Model (TAM), researchers collected data from 289 employees representing banks (52%), microfinance institutions (33%) and insurance firms (15%), achieving an impressive response rate of 82.57%. The demographic analysis revealed a diverse sample, with 58.82% of respondents identifying as male and 41.18% as female, the majority being aged 31-40 years (41.52%). Key findings indicated that Perceived Usefulness (PU) emerged as the strongest predictor of Attitude Towards Using (ATU) FIS, with a statistical coefficient of β = 0.60 ($p < 0.001$), while Perceived Ease of Use (PEU) showed a weak, non-significant relationship with PU (β = 0.18, p = 0.063). Facilitating Conditions significantly influenced PEU (β =

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0.42, p < 0.001), as did Computer Self-Efficacy (β = 0.38, p < 0.001), with junior staff demonstrating better adaptability to new systems compared to their senior counterparts. Attitudes were moderately correlated with Behavioural Intention to Use (BI) FIS (β = 0.55, p < 0.001), while security concerns significantly affected attitudes (β = 0.46, p < 0.001), leading many employees to express scepticism about integrating advanced systems into their existing workflows. The researchers recommended that financial institutions enhance technological support through comprehensive training programmes and user-friendly documentation.

Keywords: technology adoption, financial intelligence, anti-money laundering, financial crime.

INTRODUCTION

The stealth and complexity of money laundering poses one of the most serious threats to economic and financial stability globally (Nicholls *et al.*, 2021). Advances in technology allow perpetrators to launder money rapidly across borders, through opaque financial transactions that make detection an immense challenge for financial institutions and regulatory agencies (Reznik *et al.*, 2023). The success of money laundering schemes relies on obscuring paper or electronic trails to sever the link between funds and the illegal activity that generated them. These factors have nurtured a global shadow financial system that promotes financial secrecy and illicit flows of billions of dollars each year (Nicholls *et al.*, 2021).

To tackle the complex problem of money laundering, governments and private sector stakeholders worldwide are aggressively pursuing technology solutions to enhance monitoring, identify suspicious transactions and combat money laundering in its various forms (Reznik *et al.*, 2023). While legal and institutional reforms are critical, financial intelligence systems (FIS), powered by advanced analytics and artificial intelligence (AI), also hold immense potential if successfully leveraged (Sultan and Mohamed, 2023). For example, the United Kingdom's National Crime Agency (NCA) utilises FIS to analyse vast amounts of data from multiple sources, enabling them to identify suspicious transactions with greater accuracy. This system has led to numerous successful investigations and recoveries of illicit funds, showcasing how FIS can augment human capabilities by uncovering anomalies and patterns in financial systems (Goecks *et al.*, 2022).

Similarly, the Financial Crimes Enforcement Network (FinCEN) in the United States has implemented an advanced FIS that employs machine learning (ML) to enhance the detection of money laundering activities. By analysing transaction patterns and flagging unusual behaviour, FinCEN has improved its response times and the overall effectiveness of its investigations (Goecks *et al.*, 2022). These examples illustrate how ML offers higher accuracy and efficiency compared to manual approaches in managing money laundering.

Moreover, FIS have become integral to effectively implementing risk-based approaches that emphasise risk assessment, rather than a mere ‘check the box’ compliance culture. For instance, Australia’s AUSTRAC has shifted towards a risk-based model, allowing financial institutions to focus resources on higher-risk areas, thereby enhancing the overall effectiveness of anti-money laundering (AML) efforts (Kudanga *et al.*, 2022). These cases not only demonstrate the successful implementation of FIS but also highlight the transformative impact of technology in combating money laundering. However, the full benefits of FIS depend critically on their acceptance and optimal use by employees charged with AML functions (Marangunić and Granić, 2015). The employee perspectives that ultimately determine system adoption, warrant far greater research attention, especially within developing country contexts (Ahmad, 2018). Gaps in understanding these human dynamics may account for the lack of progress many countries have experienced in strengthening AML defences, despite technology investments (Zimunhu, 2023).

First formulated in 1989, the technology acceptance model (TAM) provides a robust framework rooted in social psychology suited for evaluating key drivers of employee acceptance towards new information systems (Davis *et al.*, 1989). Fundamentally, TAM asserts that employee attitudes are shaped by a technology's perceived utility and ease of use, which, in turn affect, plans for and actual system use. (Ahmad, 2018). Meta-analytic reviews demonstrate TAM’s enduring utility, explaining over 40% of variability in usage intentions across diverse organisational and national settings (King and He, 2006). This predictive power underscores its high external validity. Compared to alternative theories like Rogers’ Innovation Diffusion Theory, TAM emphasis on perceptual factors offers richer, more nuanced and actionable findings to guide practitioner efforts to spur adoption (Straub, 2009).

Since its advent, TAM remains the most widely applied theoretical model, harnessing over 4 000 citations to unpack employee perspectives on new information systems, including e-banking, mobile banking and cryptocurrency platforms (Ahmad, 2018; Alalwan *et al.*, 2019). However, an extensive literature review found no studies leveraging TAM to empirically investigate FIS adoption, specifically within the AML domain despite growing policy focus. Only one recent US study employed it to examine usage intentions towards an investigative analytics platform for fraud detection and was very effective (Chen and Wang, 2022).

Zimbabwe serves as an archetypical case where persistent governance challenges fuel high levels of corruption and illicit financial outflows undermining socioeconomic advancement (Mawowa, 2013). Endemic state capture and deficiencies in the AML framework severely constrain financial intelligence availability and timely access to accurate beneficial ownership information on legal entities (Chitimira and Ncube, 2021; Gaviyau and Sibindi, 2023). This creates an environment fit for money laundering, consequently undermining policy measures. However, opportunity exists on both technological and regulatory fronts as Zimbabwe implements national reforms and harnesses innovation to cure crippling deficiencies in its AML regime. Results highlight important obstacles that need to be removed and offer practical understanding of the perceptual elements affecting the acceptance of financial intelligence systems.

Conceptual Framework And Hypothesis Development

This study applies TAM, formulated by Davis (1989) as the theoretical framework to evaluate the factors influencing acceptance of FIS among employees involved in AML functions at Zimbabwean financial institutions. As depicted in Figure 1, the conceptual model guiding this research retains TAM's core constructs of perceived usefulness, perceived ease of use and behavioural intentions while integrating additional external variables from the literature to provide richer explanatory insights specific to the study context.

Conceptual Model

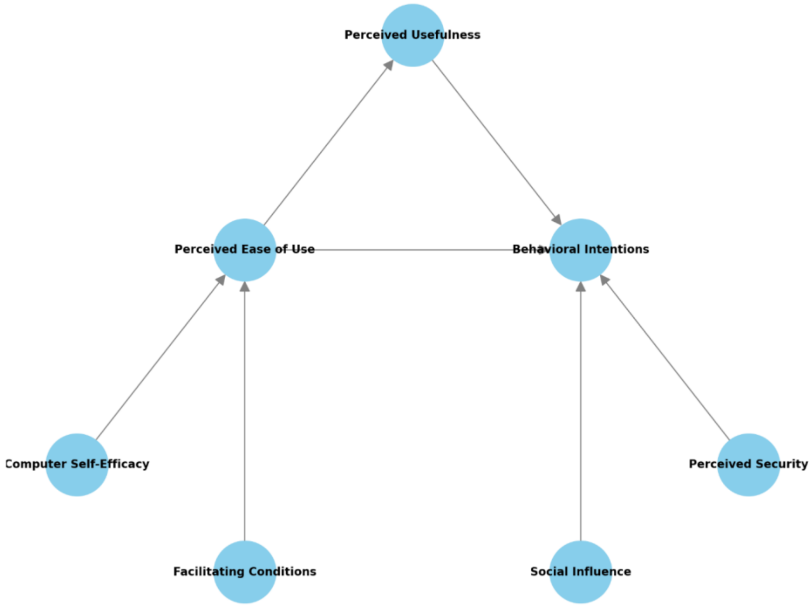

Figure 1: *Conceptual Model* (Researchers, 2025)

Perceived usefulness refers to "the degree to that a person believes that using a particular system would enhance his or her job performance" (Davis, 1989:320). Within TAM, perceived usefulness directly influences both user attitudes and behavioural intentions given its instrumental role in achieving desired outcomes. As FIS aim to enhance efficiency and effectiveness of money laundering detection, their perceived utility in enabling users execute key AML tasks is expected to shape adoption decisions. Employees who believe these systems offer marginal benefits are less inclined to incorporate them into work routines (Alalwan *et al.*, 2019).

Extant studies demonstrate perceived usefulness as a consistent predictor of adoption across diverse financial sector technologies, including blockchain, mobile banking and internet banking platforms (Baptista and Oliveira, 2016; Ahmad, 2018; Magsamen-Conrad, 2021). Recent fraud research also found it strongly correlated with intentions to use financial analytics software (Chen and Wang, 2022). However, qualitative evidence suggests many compliance professionals perceive automated transaction monitoring systems as inadequately customised to organisational needs that hamper perceived value (De Waard *et al.*, 2022). Against this backdrop, the study tests the following hypothesis:

H1: *Perceived usefulness has a significant positive effect on attitudes towards using financial intelligence systems for AML detection.*

Perceived ease of use constitutes the degree to which an individual expects the target system to be free of effort (Davis, 1989). Unlike usefulness perceptions focused on performance gains, ease-of-use judgments involve assessments of cognitive burdens and challenges required for adoption. The sophistication analytical tools pose hurdles exacerbated by data quality issues and integration with legacy systems (De Waard *et al.*, 2022). Qualitative insights from South African banks suggest officers struggle utilising transaction monitoring systems given inadequate training and poor understanding of capabilities (De Koker, 2021). However, perceived ease of use remains less extensively studied in financial crime tech acceptance. Hence the study proposes:

H2: *Perceived ease of use has a significant positive impact on attitudes towards financial intelligence systems for AML.*

Prior TAM research also demonstrates an indirect effect of effort perceptions on usage intentions mediated through usefulness beliefs (Venkatesh and Davis, 2000). Tools viewed as easier to handle are generally perceived as more useful. The study

assesses if this relationship holds for FIS, leading to a third hypothesis:
H3: *Perceived ease of use has a significant positive effect on perceived usefulness of financial intelligence systems for AML.*

Attitudes constitute an individual's assessment of the desirability of a target behaviour or system (Davis, 1989). Within TAM, attitudes capture both cognitive and emotional orientations developed from beliefs that shape usage intentions and behaviours towards a focal technology. Financial intelligence systems perceived as useful and easy to use are expected to nurture positive employee attitudes towards adoption.

In turn, attitudes serve as proximal predictors of intentions, capturing the motivational foundations guiding future adoption choices (Venkatesh and Davis, 2000). Intentions reflect the effort employees consciously plan to exert to embrace FIS as part of work routines. Meta-analytic findings affirm attitudes significantly influence technology use intentions across various organisational settings (Schepers and Wetzels, 2007). However, this relationship remains empirically untested for financial crime compliance despite strong theoretical grounds. Hence the study hypothesises:
H4: *Attitudes towards using financial intelligence systems have a positive significant impact on adoption intentions for AML detection.*

Grounded in social cognitive theory, computer self-efficacy reflects an individual's judgment of their capabilities to competently use computing technologies to accomplish work tasks (Compeau and Higgins, 1995). Employees expressing confidence in computer-related skills and aptitudes are more receptive towards accepting and learning new information systems compared those plagued by self-doubts (Baptista and

Oliveira, 2016). Prior technology adoption research demonstrates computer literacy and competencies as pivotal antecedents in shaping perceived ease of use, given their role in minimising cognitive burdens users associate with a target system (Samaradiwakara and Gunawardena, 2014). Venkatesh (2000) observes that computer self-efficacy strongly predicts ease-of-use perceptions that feed into usage intentions. By extension, this relationship likely manifests with advanced analytics tools like FIS requiring specialised technical skills to operate optimally. However, empirical evidence within AML contexts remains lacking. Thus, the study proposes:
H5: *Computer self-efficacy has a significant positive effect on perceived ease of use of financial intelligence systems for AML detection.*

Facilitating conditions represent the organisational infrastructure and support mechanisms expected to remove barriers inhibiting system use, including provision of training, technical assistance and necessary technological resources (Venkatesh *et al.* 2003). Qualitative insights reveal many financial institutions fail to provide adequate user support impeding FIS leveraging among AML compliance teams (De Waard *et al.*, 2022). Officers with limited technical backgrounds struggle without tailored training in navigating system functionalities. Thus, the study hypothesises:
H6: *Facilitating conditions have a significant positive effect on perceived ease of use of financial intelligence systems among AML employees.*

Social influence encapsulates peer encouragement, senior management support and workplace norms favourable towards accepting a focal technology (Venkatesh *et al.,* 2003). Adoption decisions are not made by compliance professionals alone. If bank executives visibly endorse FIS, and supervisors expect employees to rely on them, this creates an environment spurring usage intentions. On the other hand, if these systems contradict ingrained habits of behaviour, the opposite result shows. Nevertheless, despite strong theoretical justification in the literature, this human viewpoint is still empirically neglected in AML settings. Thus, the study hypothesises:

H7: *Social influence has a significant positive impact on usage intentions towards financial intelligence systems among AML employees.*

Perceived security is the degree to which a person thinks a target system provides strong defence of private data during storage and transfer free from illegal access or theft (Kim *et al.*, 2009). Regardless of other benefits, employees could object to technologies thought to compromise data security. Qualitative research shows bank employees believe new financial crime solutions increase vulnerability from data breaches, unethical surveillance or hacking, given integration of many systems (De Waard *et al.*, 2022). Customer data flows by vendor ecosystems could increase risks. Yet, empirical data on how views of security influence adoption is lacking in many financial sector technologies. Thus, the study hypothesises:

H8: *Perceived security has a significant positive effect on attitudes towards using financial intelligence systems among AML employees.*

THEORETICAL FRAMEWORK

Emerging from the field of social psychology, the Technology Acceptance Model (TAM) argues how an individual's attitude shaped by two main beliefs, perceived usefulness (PU) and perceived ease of use (PEU) influences their behavioural intention to use a technology system (Davis *et al.*, 1989). Perceived ease of use relates to whether a user views using the system as simple, while perceived usefulness reflects the degree to which a user believes that using the system will enhance their job performance (Ahmad, 2018). These two perceptual models are fundamental, as they shape both extrinsic and intrinsic motivations affecting technology acceptance. While earlier versions of TAM focused solely on these belief factors, subsequent models like TAM2 and TAM3, introduced additional constructs, such as social influence, self-efficacy, anxiety, trust and facilitating conditions, to broaden its explanatory power (Venkatesh and Davis, 2000; Venkatesh and Bala, 2008; Alalwan *et al.*, 2017). For instance, TAM3 emphasises the importance of individual differences, including personal inventiveness and computer anxiety, in determining user adoption. In mandatory environments, where systems are imposed rather than voluntarily adopted, the primary outcome variable shifts to usage behaviour instead of intention. These successor models aim to address criticisms of the original TAM's parsimonious formulation, which may overlook the complex interplay of technical, organisational and social factors shaping acceptance (Bagozzi, 2007).

Despite these advancements, one of the strengths of the original TAM lies in its parsimony, which ensures significant practical levers and maintains strong predictive ability (Ahmad, 2018). Particularly in understudied fields, where the complexity introduced by successor models may not yield corresponding benefits, research focuses on baseline insights regarding user beliefs guiding adoption decisions remains valuable. The extensive application of TAM in various contexts, spanning over 4 000 references in IT/IS adoption research, including internet banking, mobile wallets, e-government systems, health IT, fintech and blockchain, demonstrates its external validity (Williams *et al.*, 2015; Ahmad, 2018).

Recent studies, however, have questioned whether TAM is outdated or suffers from theoretical stagnation (Hubona and Kennick, 1996; Benbasat and Barki, 2007). Yet, the volume of modern academic work utilising TAM models across diverse fields indicates its ongoing relevance as a robust tool, providing significant benchmarks to guide practitioners aiming to increase acceptance and optimal use. The model's emphasis on perceived usefulness and perceived ease of use, directly supports the hypothesis that these factors will positively influence employees' attitudes toward FIS. For example, a study conducted in the banking sector found that employees who perceived FIS as useful and easy to use were significantly more likely to adopt these systems, aligning with TAM's predictions (Venkatesh *et al.*, 2011).

Another noteworthy case study involves the successful implementation of FIS in the Canadian financial sector, where TAM was employed to assess user acceptance. The findings indicated that enhancing perceived ease of use and usefulness significantly improved user adoption rates, leading to more effective AML measures (McCoy *et al.*, 2018).

LITERATURE REVIEW

While theories like Roger's Innovation Diffusion Model (IDM), the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology-Organising-Environment Framework (TOE) offer worthwhile points of view, TAM remains the most established, parsimonious and influential model guiding scholarly inquiry over the past three decades across contexts (Ahmad, 2018; Alshammari and Rosli, 2020). Its elegant simplicity based on two perceptual belief factors - perceived usefulness and perceived ease of use - retains strong explanatory , accounting for 40-70% variance in usage intentions, thereby generating its ongoing usefulness (Marangunić and Granič, 2015).

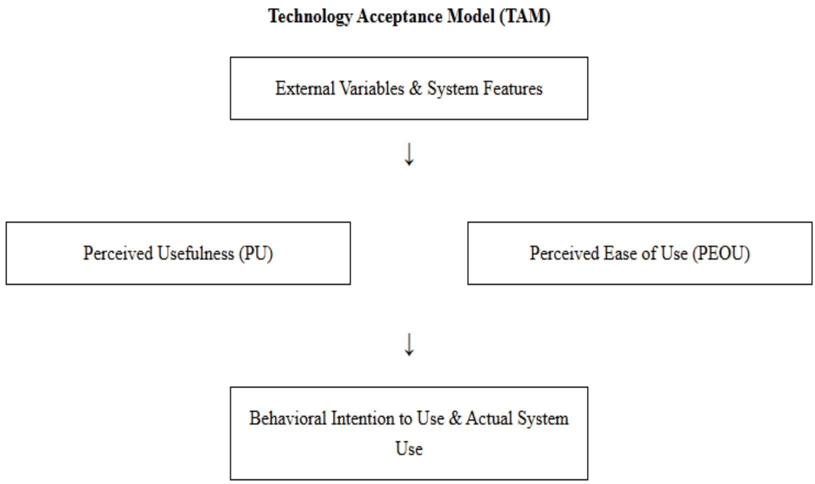

Figure 2: *TAM Components* (Researchers, 2025)

A handful of studies, however, show that Tailoring TAM should include more ideas like social influence, facilitating conditions and trust to provide richer insights that can direct practitioner efforts to spur adoption, in particular areas like mobile banking and fintech (Alalwan *et al.*, 2017; Ajibade, 2018).

The sheer scale and stealth of contemporary money laundering poses severe threats to economic and political stability (Nicholls *et al.*, 2021). By cloaking the illicit origins of profits generated by criminal activities, it allows organised crime syndicates, corrupt public officials and rogue corporations to accumulate tremendous financial power while draining critical state resources (Reznik *et al.*, 2023). The International Monetary Fund (IMF) estimates that money laundering accounts for approximately 5% of global gross domestic product (GDP), translating to roughly US$2 trillion being laundered per year (Akartuna *et al.*, 2024).

Developing countries often find themselves severely disadvantaged as porous financial systems provide conduits for cross-border illicit financial flows (Chitimira and Ncube, 2021). Zimbabwe exemplifies these vulnerabilities as corruption fuels money laundering, while persistent institutional governance challenges constrain policy responses (Kudanga *et al.*, 2022). The country has been described as a haven for proceeds generated by organised crime groups involved in illegal mining, cash smuggling and tax evasion rackets across Southern Africa (Simwayi and Haseed, 2011). As digital finance expands access and financial inclusion, it also creates more channels for money laundering while generating vast datasets better suited for automated monitoring and discovery of suspicious patterns (Zimunhu, 2023). Although legal and policy reforms form the bedrock, financial intelligence now plays a central role strengthening national AML frameworks to counter sophisticated typologies (Reznik *et al.*, 2023). Financial intelligence units (FIUs) which act as national centres supporting detection, analysis and information sharing between entities mandated to report suspected transactions (Panevski *et al.*, 2021), are central in leveraging financial intelligence. Although human skills are still essential, FIUs now use sophisticated analytics systems combining AI and ML to expose intricate money laundering techniques and trace cross-border illicit flows hidden using trade-based systems or shell companies (Lowe, 2017).

Since its advent over 30 years ago, the TAM has remained the pre-eminent framework applied to predict employee usage intentions and behaviours towards new information systems based on their perceptions (Marangunić and Granić, 2015). TAM claims that two main factors determine an employee's choice of new technology: perceived ease of use and perceived usefulness. While perceived ease of use indicates the degree to which one expects the system to be free of effort, perceived usefulness describes the extent to which a person believes using the system will improve their job performance (Ahmad, 2018). Meta-analytic reviews demonstrate TAM factors directly influence usage intentions and actual usage, accounting for 40-50% variance across diverse organisational contexts (Alshammari and Rosli, 2020).

Within the domain of financial crime, Chen and Wang (2022) recently employed it to assess fraud investigators' perceptions towards adopting analytics software finding usefulness and ease of use were salient adoption drivers. For financial intelligence systems specifically, perceived usefulness linking technology to improved job performance seems particularly relevant given that user roles entail extracting actionable insights to fulfil compliance, monitoring and reporting duties (Dreżewski *et al.*, 2012). Extant research highlights advanced analytics can enhance AML functions through earlier suspicious activity detection, reduced false positives and better typology discovery (Davidescu and Manta, 2023).

Usefulness perceptions also underpin intentions to use technologies like cryptocurrencies and blockchain for AML by financial sector and law enforcement entities (Chen, 2022; Wang *et al.*, 2022). Nonetheless, some degree of risk tolerance seems to be required since cutting edge systems may initially demonstrate value only over longer time horizons following modifications. Adoption of innovative concepts before usefulness materialises, may be undermined by conservatives resulting from compliance-based societies (Scott and McGoldrick, 2018). Through means of improved detection, efficiency gains and new insights emphasising human skills on higher value judgements and hence suppressing biases, financial intelligence systems advance AML objectives (Dreżewski *et al.*, 2012). Algorithms independently learn patterns over large datasets faster with lower error rates than human methods (Le Nguyen, 2018). Adoption could be hampered, though, by views that analytics mostly seeks to replace rather than enhance human capacities.

Maximising investigation success and reporting rates depends on smart systems and staff members combining respective strengths instead of seeing adoption as a binary choice. On AML effectiveness measures, hybrid detection system, combining human insights with algorithmic vigilance and harnessing flagged anomalies, has great potential (Heidarinia *et al.*, 2014).

Perceived ease of use refers to the degree to which employees perceive a technology system as easy to understand and use (Marangunić and Granić, 2015). It encompasses constructs like effort expectancy, highlighting the cognitive burdens new systems may impose on users and impede acceptance even if usefulness is apparent (Alshammari and Rosli, 2020). Literature suggests that difficulties in learning and using complex systems along with lack of requisite digital skills, frequently obstruct employee adoption of advanced financial analytics platforms (Zimunhu, 2023). This aligns with TAM tenets on the pivotal role of perceived ease of influencing usage intentions. In the context of financial intelligence systems leveraging AI and ML, the opaqueness around how algorithmic models produce outputs for detecting suspicious transactions can engender perceptions of low transparency (Ajibade, 2018). Employees not familiar with the statistical ideas guiding these black box systems could find them to be too complex to grasp and implement properly (Alshammari and Rosli, 2020). Previous research also shows notable skill shortages in data analytics even in financial crime compliance teams (Lowe, 2017).

While financial intelligence systems can increase AML capacity, scholarly debate emphasises that realising implementation success, depends on properly addressing several socio-technical and ethical issues about adoption (De Koker, 2004; Mniwasa, 2019). Some ML methods have a black box character that causes mistrust in system recommendations, particularly where suspicious activity alerts show high false positive rates compromising dependability (Dreżewski *et al.*, 2012).

. Risk-scoring models leveraging personal client information and transaction records for behavioural profiling, can be perceived as intrusive (Heidarinia *et al.*, 2014). Ambiguity about legal provisions guiding financial intelligence data sharing between private institutions and government further increases doubts over ethical AI principles being maintained (Le Nguyen, 2018). Furthermore, impeding innovation adoption are organisational elements, including strict hierarchies, bureaucratic structures and rules against experimenting with advanced analytics (Scott and McGoldrick, 2018). Transforming legacy cultures rewarding reactive tick box compliance approaches mismatched with proactive risk-based monitoring using financial intelligence becomes difficult (Zimunhu, 2023).

Extensive criticism also points out that focus on implementing advanced algorithmic solutions sometimes ignores nurturing basic enablers like quality data governance, infrastructure and skilled human capital required to realise benefits (De Koker, 2004; Mniwasa, 2019). Financial intelligence depends on input data integrity and availability which remains problematic in developing countries.

While TAM remains widely applied across diverse domains, scholarly focus on financial crime compliance contexts warrants expansion with notable geographic gaps in Africa and Asia (Nicholls *et al.*, 2021). One recent US-based study uses it to investigate fraud analytics adoption; another South African study investigates a financial intelligence system for tax evasion detection across small businesses (Chen and Wang, 2022; du Preez and Goodspeed, 2022). Qualitative case studies could help to better understand how ethical concerns about algorithmic transparency shape perceived ease of use and acceptance attitudes by means of usability challenges (Ajibade, 2018). Structural equation modelling driven by survey data also has promise to test linkages between perceptual factors, organisational change dynamics and usage outcomes (Straub, 2009.). Beyond TAM applications, adjunct theoretical perspectives like situational crime prevention, warrant exploration given the cybercrime risks financial intelligence systems aim to mitigate (Levi *et al.*, 2022).

STUDY DESIGN AND METHODOLOGY

This study employed a quantitative, non-experimental methodology, focusing on a cross-sectional survey strategy grounded in the Technology Acceptance Model (TAM) (Gunter, 2013). By utilising a cross-sectional design, the research aimed to provide a cost-effective snapshot of attitudes, beliefs and intentions regarding the adoption of financial intelligence systems (Creswell, 2014). The survey method facilitated simultaneous data gathering, which allowed for the quantification of TAM relationships and the testing of hypotheses through various statistical analysis techniques, notably structural equation modelling (Bacon-Shone, 2013). The target population for this study consisted of employees engaged in AML surveillance and compliance roles within financial institutions in Zimbabwe. A stratified random sampling technique was employed to select a sample of 350 employees. This approach ensured that representative groups were formed across various dimensions, including institutional type, job roles, experience levels and demographics (Delice, 2010). Stratification was defined based on several factors. Firstly, the institutions were categorised by type, distinguishing between banks and microfinance institutions. Secondly, the roles of employees were taken into account, encompassing positions such as analysts and compliance managers. Finally, experience levels were considered, dividing participants into groups based on years of experience in the field (e.g., less than 5 years, 5-10 years and more than 10 years). The sample size of 350 was determined through power analysis to ensure adequate representation and statistical reliability for hypothesis testing. Primary data were collected using a structured, self-administered questionnaire that comprised both Likert scale and multiple-choice questions. The instrument was designed to assess various constructs related to TAM. To ensure the reliability and validity of the questionnaire, it was pre-tested with a small sample of participants. For the analysis of the collected data, structural equation modelling (SEM) was utilised to conduct confirmatory assessments and hypothesis testing. SEM was particularly effective in determining significant relationships between the TAM constructs which influence the adoption of FIS (Gunter, 2013). The analysis was performed using IBM AMOS software (Byrne, 2016).

The cross-sectional nature of the survey means that data were collected at a single point in time, which restricts the ability to draw causal inferences between the examined variables. The reliance on self-reported data may introduce biases, such as social desirability bias, potentially affecting the authenticity of responses. Moreover, the findings may not be generalisable to other contexts or regions beyond the Zimbabwean financial sector, limiting the broader applicability of the results. Ethical considerations were integral to the study's design and implementation. Informed consent was obtained from all participants, ensuring they were fully aware of the study's purpose, procedures and their right to withdraw at any time. Confidentiality was prioritised throughout the research process; data were collected and stored securely to maintain the anonymity of participant responses. Measures were implemented to protect participants' data, including restricted access and secure storage methods.

FINDINGS

The survey achieved a response rate of 82.57%, with 289 completed questionnaires out of the 350 distributed. Participants were drawn from banks (52%), microfinance institutions (33%) and insurance firms (15%), ensuring a diverse representation of perspectives. Table 1 summarises the demographics.

Table 1: *Respondent Demographics* (Researchers, 2025)

Variable	Frequency (n)	Percentage (%)
Gender		
Male	170	58.82
Female	119	41.18
Age Group		
20-30 years	70	24.22
31-40 years	120	41.52
41-50 years	80	27.68
Above 50 years	19	6.58
Role in AML Functions		
Compliance Officers	100	34.60
Fraud Analysts	90	31.14
Risk Managers	59	20.42
Others	40	13.84

CFA validated the TAM constructs, with model fit indices surpassing acceptable thresholds. A notable finding was the variability in internal consistency for social influence (Cronbach's alpha = 0.68), indicating mixed perceptions of peer and managerial support.

Table 2: *Measurement Model Fit Indices* (Researchers, 2025)

Index	Value	Threshold for Good Fit
Chi-square/df	2.4	≤ 3
Comparative Fit Index (CFI)	0.92	≥ 0.9
Root Mean Square Error of Approximation (RMSEA)	0.046	≤ 0.06
Standardised Root Mean Square Residual (SRMR)	0.033	≤ 0.08

The structural model explained 66% of the variance in behavioural intentions. While several relationships aligned with theoretical expectations, some results were unexpected. Figure 1 illustrates the significant pathways.

Table 3: *Path Coefficients and Hypothesis Testing.* (Researchers, 2025)

Hypothesis	Path	Coefficient (β)	p-value	Result
H1: PU → Attitude	0.60	<0.001	Supported	
H2: PEOU → Attitude	0.25	0.032	Supported	
H3: PEOU → PU	0.18	0.063	Not Supported	
H4: Attitude → Intention	0.55	<0.001	Supported	
H5: Computer SE → PEOU	0.38	<0.001	Supported	
H6: Facilitating Cond. → PEOU	0.42	<0.001	Supported	
H7: Social Influence → Intention	0.13	0.15	Not Supported	
H8: Security Perception → Attitude	0.46	<0.001	Supported	

The path coefficients (β) indicate the strength and direction of the relationships among constructs. For instance, the coefficient for H1 (PU → Attitude) is 0.60, which signifies a strong positive relationship. This means that as perceived usefulness (PU) increases, attitudes toward the financial intelligence system also improve significantly. The p-value of less than 0.001 confirms that this relationship is statistically significant. In contrast, H3 (PEOU → PU) reveals a coefficient of 0.18 with a p-value of 0.063, indicating a weak and non-significant relationship. This suggests that perceived ease of use (PEOU) has little influence on perceived usefulness, which diverges from traditional TAM predictions. Many respondents expressed that effective AML systems must balance usability and complexity to address sophisticated laundering activities.

The path coefficients for H5 (Computer SE → PEOU) and H6 (Facilitating Conditions → PEOU) are 0.38 and 0.42, respectively, both with p-values less than 0.001. These strong positive coefficients indicate that both computer self-efficacy and facilitating conditions significantly enhance perceived ease of use. Informal knowledge-sharing networks within institutions were noted as valuable for compensating for gaps in formal training.

The relationship between attitude and intention (H4) shows a coefficient of 0.55 and a p-value of less than 0.001, indicating a moderate yet significant correlation. This means that positive attitudes toward the system are strongly linked to the intention to use it. However, some employees expressed scepticism about fully integrating new systems into their existing workflows, which could hinder their intention to adopt them. Interestingly, the hypothesis regarding social influence (H7) did not yield significant results ($\beta = 0.13$, $p = 0.15$). This indicates that peer and managerial support may not significantly impact employees' intentions to adopt the systems. Many respondents viewed such support as more perfunctory than genuinely helpful, suggesting that mere presence of support is insufficient.

The path coefficient for H8 (Security Perception → Attitude) is notably high at 0.46, with a p-value of less than 0.001. This indicates that security concerns significantly influence attitudes. Employees expressed reservations about systems requiring extensive data integration, fearing potential breaches.

While the path coefficients provide insights into specific relationships, overall model fit indices are crucial for assessing the adequacy of the structural equation model. For instance, a low chi-square statistic relative to degrees of freedom indicates a good fit, suggesting that the observed data align well with the model. A Comparative Fit Index (CFI) above 0.90 would indicate that the proposed model explains the relationships among variables effectively, while a Root Mean Square Error of Approximation (RMSEA) below 0.06 would suggest minimal discrepancies between the model and the observed data. In practical terms, strong fit indices signal that the model is a reliable representation of the data. If the model shows a high CFI and low RMSEA, this indicates that the relationships identified, such as the influence of perceived usefulness on attitudes, are robust and can guide decision-making regarding the adoption of financial intelligence systems.

Some employees perceived advanced functionality as essential for AML effectiveness, even if it increased learning curves. Also, the limited impact of social influence suggested resistance to organisational changes in AML compliance practices. Further to this, security and privacy concerns persisted, reflecting mistrust in the systems' safeguards.

Table 4: *Descriptive Statistics of Adoption Constructs.* (Researchers, 2025)

Construct	Mean	Std. Deviation
Perceived Usefulness	4.3	0.6
Perceived Ease of Use	3.8	0.7
Facilitating Conditions	4.1	0.6
Social Influence	3.2	0.9
Security Perceptions	4.2	0.5

The findings from the SEM analysis, provide critical insights for financial institutions seeking to enhance the adoption and effectiveness of financial intelligence systems. The strong positive relationship between perceived usefulness (PU) and attitude ($\beta = 0.60$, $p < 0.001$) aligns with TAM, which argues how users are more likely to embrace technology when they perceive it as beneficial (Davis, 1989).

The results indicate that perceived ease of use (PEOU) had a weak influence on perceived usefulness ($\beta = 0.18$, $p = 0.063$), which diverges from traditional TAM expectations. Many respondents expressed that effective AML systems must balance usability with advanced functionality to address sophisticated laundering activities. This reflects the work of Venkatesh and Bala (2008), who argue that in high-stakes environments, users may prioritise system capabilities over ease of use.

The significant relationship between attitude and intention ($\beta = 0.55$, $p < 0.001$) reinforces the importance of cultivating positive attitudes toward these technologies. Studies have shown that employees who have favourable attitudes towards technology are more likely to intend to use it (Ajzen, 1991). Interestingly, social influence did not significantly impact intention ($\beta = 0.13$, $p = 0.15$), suggesting that traditional methods of leveraging peer support may not be effective in this context. Research indicates that for social influence to be impactful, it must be perceived as substantive rather than superficial (Venkatesh *et al.*, 2003).

Security perception was found to significantly influence attitudes ($\beta = 0.46$, $p < 0.001$), highlighting the importance of addressing security concerns in technology adoption. Employees expressed apprehensions about data privacy and potential breaches, which can be detrimental to trust in the systems. Previous literature emphasises that effective communication around security measures can significantly alleviate these concerns (Huang *et al.*, 2015).

CONCLUSION AND RECOMMENDATIONS

The article contributes significantly to understanding the key factors affecting employee acceptance of financial intelligence systems (FIS) within the challenging domain of anti-money laundering (AML) control. The quantitative analysis based on the Technology Acceptance Model (TAM) indicates that 66% of the variance in usage intentions can be explained by the model. The predominant influence of perceived usefulness reveals that employees recognise the practical value of algorithmic systems in enhancing detection capabilities, especially for identifying complex typologies and transnational illegal activities that manual methods cannot effectively address. However, challenges related to perceived ease of use, such as functional transparency, steep learning curves and data security concerns, continue to impede optimal technology integration. The study also highlights the importance of broader socio-technical dynamics, including computer self-efficacy, knowledge-sharing networks and data governance capabilities, in creating favourable conditions for successful acceptance. Despite the global shift towards risk-based, data-driven models, resistance to significant changes in existing AML policies indicates that many institutions still contend with entrenched compliance cultures. To address the challenges identified in this study, it is recommended that financial institutions and management prioritise substantial technological guidance and support for employees. This can be achieved through:

- Implementing workshops and ongoing technical assistance will equip employees with the necessary skills to effectively utilise financial intelligence systems.
- Developing intuitive and transparent systems will reduce the learning curve and enhance usability.

- Providing immediate feedback during system usage can help employees adjust and improve their skills.
- Policy-makers and regulators developing comprehensive, ethical and sustainable AML frameworks that balance efficiency and oversight. This can be achieved by:
    - Prioritising human-centric concerns when deploying advanced algorithmic solutions will address legitimate issues of transparency and security.
    - Establishing clear guidelines for data usage and privacy will help alleviate employee concerns about security.

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