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Bridging Technology and Sales Performance: How Self-Efficacy and Lead Qualification Shape Adaptive Selling in Uganda's Insurance Industry

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Abstract

In Uganda's insurance sector, salespersons' ability to tailor their strategies to customer needs is a key driver of success. This study examines how Technology Self-Efficacy (TSE) influences the relationship between Lead-Qualification Skills (LQS) and Adaptive Selling Behaviour (ASB). Using a cross-sectional quantitative approach, data were collected from 364 licensed sales agents through structured questionnaires across various insurance companies. Correlation and regression analyses were performed, with the Hayes Process Macro applied to test the moderating effect of TSE. The results indicate that both LQS and TSE are positively associated with ASB, and regression analysis confirms their significant predictive roles. Moreover, TSE strengthens the link between LQS and ASB, enhancing salespersons' capacity to adjust their selling approaches effectively. These findings contribute to the literature on adaptive selling in Uganda by emphasizing the combined importance of technological confidence and lead-management proficiency. The study recommends that insurance firms prioritize training programs that develop these competencies to boost adaptive selling performance in an increasingly dynamic market.

Keywords: Lead qualification skills, Salesperson, Adaptive selling behaviour, Insurance firms, Technology self-efficacy, Uganda

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Introduction

In today's fast-moving global business environment, where market demands, consumer preferences, and technological innovations constantly evolve, the ability of sales professionals to adapt their approaches has become a crucial determinant of organizational success. Adaptive Selling Behaviour (ASB) enables sales personnel to modify their strategies to align with changing conditions, thereby maintaining competitiveness [1, 2]. Beyond improving sales effectiveness, this agility strengthens client relationships and fosters loyalty, which is essential for long-term growth. Developing adaptive selling skills should therefore be a priority in sales training initiatives, ensuring that personnel can navigate the challenges of dynamic and unpredictable markets while effectively addressing diverse customer needs [1]. By tailoring strategies to the cultural, economic, and technological contexts of their clients, sales professionals can enhance customer satisfaction and cultivate loyalty [3].

Being responsive to the specific characteristics of different market segments allows salespeople to exceed customer expectations, building enduring relationships that support sustainable business performance [1]. Chawla *et al.* [4, 5] highlight that adaptive selling fosters flexibility in communication and sales techniques, improving relational quality and customer contentment. Moreover, collecting and analyzing customer data informs strategic decisions and allows proactive adjustments in sales tactics. Continuous learning and awareness of market dynamics equip sales personnel to anticipate shifts and innovate approaches, positioning them for success in competitive environments [4, 5].

In Uganda, the Insurance Regulatory Authority (UIRA) has emphasized the need for flexibility in sales approaches, particularly given that insurance is widely considered an unsought product [6]. The country's low insurance penetration, currently at 0.8%, highlights the need for adaptive strategies to increase uptake [7, 8]. Despite this, many insurers continue to rely on conventional, face-to-face sales practices, reflecting a resistance to change that limits responsiveness to evolving customer demands [8, 9]. This reliance on outdated methods, compounded by paper-based record-keeping, constrains scalability and limits access, particularly in rural areas where underinsurance is prevalent. Sales professionals often fail to tailor solutions to individual client circumstances, underscoring the need for more agile and personalized sales approaches [6].

Effective lead-qualification skills (LQS) have been identified as a key factor in promoting ASB. Research demonstrates that strong LQS enables sales personnel to identify, prioritize, and respond to the specific needs of individual clients, enhancing flexibility in sales interactions [10-12]. Experienced salespeople tend to maintain a repertoire of "if-then" rules that guide strategic adjustments in response to varying customer scenarios, thereby supporting adaptive selling [1, 13, 14]. According to adaptive selling theory, sales strategies should be continuously adjusted to reflect customer requirements and situational factors, with lead-qualification competencies serving as a foundation for this adaptability [15-17].

Technology Self-Efficacy (TSE) further strengthens the impact of LQS by enabling sales personnel to confidently use digital tools and platforms for analyzing leads and customizing approaches. High TSE allows salespeople to leverage CRM systems and analytics for more precise segmentation and targeted strategies, amplifying adaptive selling outcomes. Park *et al.* [18] note that while Sales Force Automation tools provide essential resources, their effectiveness depends on how adeptly sales personnel utilize them. Research suggests that LQS alone may not fully account for ASB unless combined with technological proficiency [19, 20]. The Technology Acceptance Model (TAM) further highlights that perceived ease of use and usefulness drive adoption, emphasizing the value of simple, efficient systems [21]. Despite this, studies have yet to fully examine TSE as a moderating factor in the relationship between LQS and ASB.

Prior research shows mixed results regarding the LQS-ASB link, reflecting differences in methodology, theoretical orientation, and contextual settings. This variability underscores the need for further investigation into how LQS interacts with other factors, such as TSE, to enhance adaptive selling [22]. The present study addresses this gap by focusing on insurance salespersons in Uganda, examining the influence of LQS on ASB and the moderating role of TSE. Findings indicate that combining strong lead-qualification skills with high technological confidence significantly boosts adaptive selling capacity. These insights extend the theoretical understanding of ASB and offer practical guidance for sales strategies in emerging markets.

The remainder of this paper outlines the theoretical framework, reviews empirical literature to support hypothesis development, describes the research methodology, presents and interprets findings, and concludes with a discussion of practical implications for the insurance sector.

Literature Review

Theoretical foundation

This study develops an integrated framework by combining Adaptive Selling Behaviour (ASB) Theory, Categorization Theory, and the Technology Acceptance Model (TAM) to examine how sales professionals adjust strategies in dynamic markets. ASB Theory [17] highlights that effective salespeople must continuously modify their approaches to meet the distinct needs of different clients. However, the theory does not provide clear guidance on how to systematically classify customers, which can result in inconsistent application of adaptive strategies. To address this limitation, Categorization Theory [23] is introduced, offering a method for grouping clients based on shared attributes. This enables salespeople to apply structured strategies to each category while retaining the flexibility to adjust as needed. Nevertheless, such categorization may overlook unique individual differences, signaling the need for ongoing refinement in adaptive practices.

The TAM framework [21] complements these theories by emphasizing the enabling role of technology. Salespeople's perceptions of the usefulness and usability of digital tools, such as CRM systems, influence their adoption and effective use in managing customer information. Leveraging these tools allows for more precise and timely adjustments to sales approaches based on categorized client data. Together, these theories create a cohesive framework: ASB Theory underscores the necessity of flexibility, Categorization Theory organizes customer insights, and TAM facilitates the technological implementation of adaptive strategies. This integrated perspective provides a comprehensive foundation for conceptualizing adaptive selling in contemporary, technology-driven sales environments and guides the formulation of hypotheses for empirical testing.

Empirical literature

ASB and LQS

Adaptive Selling Behaviour (ASB) refers to a salesperson's skill in adjusting sales approaches to meet the unique preferences and cultural characteristics of each client. Recent research indicates that ASB is closely intertwined with Lead-Qualification Skills (LQS) [24]. Drawing on the principles of ASB Theory [17] and Categorization Theory [23], LQS allows sales professionals to assess potential clients, prioritize leads, and refine strategies based on actionable customer insights [25]. Studies suggest a mutually reinforcing relationship: well-developed LQS provides the foundation for adaptive selling by informing strategy customization, while the practice of ASB enhances the accuracy and effectiveness of lead qualification through ongoing client interactions [26].

This interaction becomes particularly significant in digital and cross-cultural sales environments. For example, Majeed *et al.* [27] show that integrating social media analytics with LQS can help bridge cultural differences and optimize engagement in global markets. At the same time, reliance on rigid lead-qualification processes may hinder creative problem-solving in dynamic retail contexts [28], emphasizing the need to balance structured procedures with flexibility. In emerging markets, where customer needs are highly heterogeneous, understanding this balance is critical for effective sales performance [1]. Based on these insights, the following hypothesis is proposed:

H1: Lead-Qualification Skills (LQS) positively affect Adaptive Selling Behaviour (ASB).

TSE and ASB

Technology Self-Efficacy (TSE), derived from Bandura's social cognitive theory [29], has emerged as a crucial factor in modern digital sales environments. Sales personnel with high TSE are able to effectively utilize tools such as Customer Relationship Management (CRM) systems and social media platforms to gather customer insights, tailor interactions, and dynamically adjust their sales strategies [3]. The Technology Acceptance Model (TAM) further elucidates this relationship, suggesting that when salespeople perceive digital tools as intuitive and valuable, TSE enhances their capacity to transform customer data into targeted, client-focused strategies [21, 30, 31].

Nonetheless, the use of technology in sales also introduces ethical considerations. While TSE can improve personalization and the precision of sales pitches [1], excessive or poorly managed personalization may raise privacy concerns and undermine customer trust. Similarly, Román and Rodríguez [31] emphasize that the benefits of TSE are contingent on organizational support, including training programs that combine technical skills with ethical guidelines. These insights highlight TSE's dual role: it acts as a facilitator of adaptive selling but can also present limitations if technological capabilities are not implemented responsibly.

Drawing on these theoretical and empirical perspectives, the study proposes the following hypothesis:

H2: Technology Self-Efficacy (TSE) positively influences Adaptive Selling Behaviour (ASB).

The moderating role of TSE

The impact of Lead-Qualification Skills (LQS) on Adaptive Selling Behaviour (ASB) is significantly influenced by a salesperson's confidence in using technology, or Technology Self-Efficacy (TSE). Salespeople who are adept with digital tools can analyze and interpret lead information more effectively, allowing them to craft tailored strategies that address client-specific needs with greater precision than those with lower technical proficiency [1, 32, 33]. Research by Román and Rodríguez [31] suggests that TSE reduces mental effort in processing lead data, enabling sales professionals to devote attention to understanding subtle interpersonal dynamics.

Nevertheless, the moderating role of TSE is nuanced. Compeau and Higgins [34] note that insufficient technological confidence can hinder adaptive selling, whereas overdependence on automation may suppress the judgment and creativity required for complex client interactions. Similarly, Chawla *et al.* [4] highlight that TSE yields the greatest benefits when paired with relational skills, such as empathy, which ensure that technology supports rather than replaces human engagement. This underscores the importance of integrating both technical and interpersonal competencies to strengthen the effect of LQS on ASB.

Overall, current evidence points to a dynamic interplay among LQS, TSE, and ASB, emphasizing their combined role in enhancing adaptive sales performance. Based on this understanding, the study proposes the following hypothesis:

H3: Technology Self-Efficacy (TSE) moderates the relationship between Lead-Qualification Skills (LQS) and Adaptive Selling Behaviour (ASB).

The conceptual framework reflecting these relationships is illustrated in **Figure 1**.

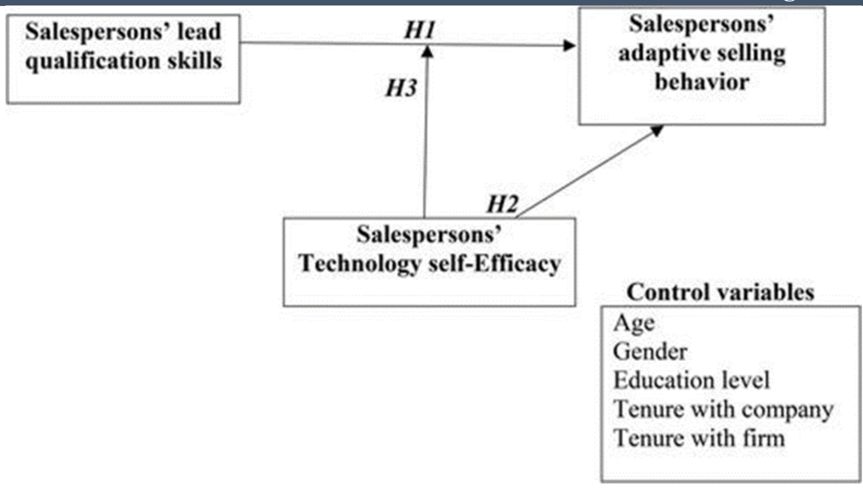

Figure 1. Conceptual model Source: Hayes [22]

Methodology

Research design

This study is situated within the Ugandan insurance industry. Although a mixed-methods approach with a longitudinal design could have provided a deeper understanding of the variables and their interrelationships over time [35], practical constraints related to time and budget necessitated the adoption of an explanatory research design. A cross-sectional quantitative approach was employed, allowing the investigation of relationships among variables at a single point in time, which offered a cost-effective and efficient method for data collection and analysis.

Sample size, sampling procedure and study population

The study focused on licensed salespersons within Uganda's insurance industry, which, according to the Uganda Insurance Regulatory Authority [8], numbers 3,278 individuals. Sales personnel were chosen as the target population due to their central role in driving organizational sales performance [36]. To determine an appropriate sample size, Krejcie and Morgan's (1970) table was employed, resulting in 364 participants. This approach is widely accepted for its statistical robustness, as it accounts for population size, desired confidence intervals, and margin of error, ensuring that the sample is both representative and reliable. Allocation across firms was calculated using the formula: sample size = $(P/X) \times Y$, where P represents the number of salespersons in a specific company, X is the total population, and Y is the overall sample size.

To enhance representativeness, a proportionate stratified random sampling method was adopted. The full population was first divided into strata corresponding to each insurance firm, with sample sizes for each stratum proportionate to the firm's share of the total population. Larger firms thus contributed more participants than smaller ones, reflecting their relative presence in the sector. Within each stratum, individuals were randomly selected, minimizing bias and ensuring that the sample captured the diversity and variability of the broader population. This method strengthens the reliability and generalizability of the study's findings [37].

Ethical statement

This study was conducted in full compliance with the ethical requirements specified by the journal. It forms part of the author's doctoral research and received formal clearance from Moi University, the affiliating institution. In addition, the Insurance Regulatory Authority (IRA) of Uganda issued an official letter of support (IRA 2023/05/15), validating the study's relevance and permitting data collection. Branch managers were subsequently informed of this approval and assisted in coordinating the participation of sales personnel for the research.

Statement of consent

This research included human participants, and in line with the journal's ethical guidelines, informed consent was secured. In certain circumstances, the authors deemed verbal consent appropriate and justified. Participants provided their agreement verbally after receiving detailed explanations about the study's objectives, procedures, and their role in the research.

Rationale for using verbal consent

This research was conducted as part of the corresponding author's doctoral study. Given the time constraints associated with the project, verbal consent was adopted as a practical method to ensure that participants were fully informed and voluntarily

agreed to take part without the need for written forms. Participants were briefed on the study's objectives and procedures and confirmed their
willingness to participate. To maintain confidentiality, no personal identifiers, such as names, were recorded on the questionnaires, safeguarding participants' privacy.

Data collection instrument and process

The study employed a structured questionnaire with a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), with intermediate values of 2 (disagree), 3 (neutral), and 4 (agree). Adjustments were made to certain items to better reflect the local context, ensuring that responses were meaningful and comparable to prior research findings [38, 39].

Lead-Qualification Skills (LQS) were measured using six items adapted from Román and Iacobucci [10], Román and Rodríguez [31], and Zhou and Charoensukmongkol [11], evaluating the respondents' ability to identify customer needs and buying motivations. Adaptive Selling Behaviour (ASB) was measured using seven items based on Spiro and Weitz [40], while Technology Self-Efficacy (TSE) was assessed through seven items adapted from Ellen *et al.* [41] and Cho and Chang [42]. The study also included five control variables: gender, age, educational level, overall sales experience, and tenure within the current organization.

The instrument's validity was established through expert evaluation and the use of a content-validity index. Reliability testing via Cronbach's alpha confirmed internal consistency, with all values exceeding the recommended threshold of 0.7 (Amin). Factor analysis was conducted to ensure that the questionnaire items adequately represented the intended constructs, with factor loadings above 0.5. In addition, discriminant validity was assessed to confirm that each construct measured a distinct concept, further supporting the robustness of the instrument.

Common method bias testing

To reduce worries about common method variance stemming from relying solely on self-report measures, we applied Harman's one-factor test [43]. The unrotated principal component analysis revealed that a single factor captured just 36.7% of the overall variance—far less than the 50% cutoff typically used—indicating that common method bias is unlikely to be a serious concern in this study.

Data analysis

The data analysis was carried out using SPSS version 26. Initially, Pearson correlation coefficients were computed to examine the relationships among the study variables. Subsequently, Hayes' Process Macro Model 4 [44] was employed to assess the predictive power of the independent variables on the dependent variable and to test the moderating effect of salesperson Technology Self-Efficacy (TSE) on the relationship between Lead-Qualification Skills (LQS) and Adaptive Selling Behaviour (ASB). Model 4 is widely recognized for its ability to investigate both the conditions and mechanisms through which effects occur, providing a nuanced understanding of the interactions between variables and enhancing the rigor of empirical analysis.

Results

Descriptive statistics and validity results

The study aimed to examine whether Technology Self-Efficacy (TSE) moderates the relationship between salesperson Lead-Qualification Skills (LQS) and Adaptive Selling Behaviour (ASB). The analysis utilized a dataset of 328 completed questionnaires, yielding a response rate of 95% from a targeted sample of 346 participants. This exceeds the 70% minimum response rate suggested by Baruch and Holtom [45], indicating strong participant engagement. **Table 1** presents descriptive statistics, including means, standard deviations, validity and reliability measures, as well as the correlation coefficients among the study variables.

Table 1. standard deviation, Mean, validity, correlation results and reliability

Construct	Mean	SD	Discriminant Validity (√AVE)	Composite Reliability	1	2	3
1. Adaptive selling behavior	2.63	0.23	0.822	0.790	1		
2. Lead qualification skills	3.81	0.41	0.785	0.814	0.419	1	
3. Technology self-efficacy	3.98	0.52	0.757	0.791	0.291	0.203	1

Note: Correlation is significant at the 0.01 level (2-tailed). Source: Primary data 2024.

The analysis revealed that salespersons' Adaptive Selling Behaviour (ASB) had a mean score of 2.63 (SD = 0.23), indicating some level of adaptability but highlighting considerable room for improvement. Lead-Qualification Skills (LQS) and Technology Self-Efficacy (TSE) exhibited higher mean scores of 3.81 (SD = 0.41) and 3.98 (SD = 0.52), respectively, reflecting strong proficiency in these areas. Based on conventional interpretations of Likert scale responses, these results suggest moderate-to-high competency in LQS and TSE, while ASB remains relatively underdeveloped [46]. These findings align with the principles of Adaptive Selling Theory [17], which emphasize the importance of combining strong skills and technological confidence with actual adaptive selling performance.

To ensure the robustness of the measurements, both validity and reliability were evaluated. Construct validity coefficients were 0.822 for ASB, 0.785 for LQS, and 0.757 for TSE, indicating that the survey items effectively captured the intended constructs. Reliability, assessed using Cronbach's alpha, yielded scores of 0.790 for ASB, 0.814 for LQS, and 0.791 for TSE, all exceeding the 0.70 threshold and demonstrating consistent responses across participants.

Relationships among variables were examined using Pearson's correlation coefficient. ASB was positively correlated with LQS ($r = 0.419$, $p < 0.01$) and TSE ($r = 0.291$, $p < 0.01$), suggesting that higher adaptive selling behaviour is associated with stronger lead-qualification skills and greater technological self-efficacy. These results support Hypothesis 1, indicating that salespersons who are adept at qualifying leads are better able to understand customer needs and tailor their approaches accordingly. Similarly, Hypothesis 2 was confirmed, showing that salespersons with higher TSE are more capable of leveraging digital tools to gather customer insights, monitor interactions, and adjust their selling strategies, thereby enhancing adaptability in technology-driven sales environments.

Discriminant validity was also assessed using the Fornell-Larcker criterion and the HTMT ratio. All HTMT values were below the 0.90 threshold, confirming that ASB, LQS, and TSE are distinct constructs. Additionally, the square roots of the Average Variance Extracted (AVE) for all variables exceeded their inter-construct correlations, further supporting discriminant validity and demonstrating that each construct is measured independently and accurately [46].

Table 2. Discriminant validity results

Construct Pair	Pearson Correlation	Heterotrait-Monotrait (HTMT) Ratio
Adaptive Selling Behavior ↔ Lead Qualification Skills	0.419	0.522
Adaptive Selling Behavior ↔ Technology Self-Efficacy	0.291	0.368
Lead Qualification Skills ↔ Technology Self-Efficacy	0.203	0.253

Source: Primary data, 2025.

Multiple regression analysis

To examine the factors influencing salespersons' Adaptive Selling Behaviour (ASB), three separate regression models were tested, each incorporating a different set of predictor variables. The outcomes of these analyses are summarized in **Table 3**, which details the estimated beta coefficients, t-statistics, R^2 values, changes in R^2, F-statistics, and significance levels for each model, providing a comprehensive overview of how the independent variables contribute to explaining variations in ASB.

Table 3. Multiple regression model

Independent Variable	Model 1		Model 2		Model 3	
	Standardized β	t-value	Standardized β	t-value	Standardized β	t-value
Gender	0.07	0.02	0.01	0.06	0.03	0.15
Age	0.29	2.03	0.52	7.12	0.61	0.34
Education level	0.31	3.32	0.81	5.02	0.24	0.38
Tenure with company	0.03	0.08	0.09	0.04	0.02	0.05
Tenure in the sector	0.09	0.08	0.01	0.01	0.06	0.03
Lead qualification skills			0.301***	7.02		
Technology self-efficacy					0.320***	

Note: N = 328. *p < 0.05, **p < 0.01, ***p > 0.001. Source: Primary data 2024.

Model 1 consisted solely of control variables (age, gender, organizational tenure, education level and industry tenure). This baseline model was not statistically significant ($F = 0.23$, $p = 0.689$) and explained only a modest portion of the variance in adaptive selling behavior ($R^2 = 0.08$). Within this model, only age ($\beta = 0.29$, $t = 2.03$, $p < 0.05$) and education level ($\beta = 0.31$, $t = 3.32$, $p < 0.05$) reached statistical significance, suggesting that older and more highly educated salespeople tended to exhibit greater adaptive selling behavior. The remaining controls—gender ($\beta = 0.07$, $t = 0.02$), tenure with the company ($\beta = 0.03$, $t = 0.08$), and tenure in the sector ($\beta = 0.09$, $t = 0.08$)—were not significant.

Model 2 built on the controls by adding salespeople's lead-qualification skills as a predictor. This addition markedly improved model performance, raising R^2 to 0.101 ($\Delta R^2 = 0.021$) and rendering the overall model highly significant ($F = 19.902$, $p < 0.001$). Lead-qualification skills proved to be a strong positive predictor of adaptive selling behavior ($\beta = 0.301$, $t = 7.02$, $p < 0.001$), showing that salespeople who are better at assessing and prioritizing leads are also more effective at tailoring their sales approach to individual customers.

Model 3 incorporated all variables simultaneously, including both lead-qualification skills and technology self-efficacy, alongside the demographic controls. This full model exhibited substantially greater explanatory power, with R^2 rising to 0.201 ($\Delta R^2 = 0.180$ from Model 1) and explaining approximately 20% of the variance in adaptive selling behavior. The model was highly significant ($F = 28.971$, $p < 0.001$). In this comprehensive specification, technology self-efficacy emerged as a particularly strong driver of adaptive selling ($\beta = 0.320$, $t = 8.82$, $p < 0.001$), underscoring that salespeople who feel confident using technology are considerably more likely to adjust their selling strategies flexibly. Lead-qualification skills retained their significant positive effect, while age and education continued to show influence in some specifications, though gender, organizational tenure, and industry tenure remained non-significant throughout.

The moderating effect of TSE

To examine the moderating role of technology self-efficacy (TSE), we employed Hayes' PROCESS Macro v4.0 (Model 1) developed by Hayes [22]. All procedures followed the standardization and mean-centering recommendations for moderation testing outlined by Aiken and West [47]. The results of the moderation analysis are displayed in **Table 4**.

The analysis revealed a significant positive direct effect of lead qualification skills (LQS) on adaptive selling behavior (ASB) ($\beta = 0.295$, $t = 6.081$, $p < .001$). Additionally, technology self-efficacy (TSE) exerted a strong positive direct effect on ASB ($\beta = 0.442$, $t = 6.241$, $p < .001$). More importantly, the interaction term (LQS × TSE) was statistically significant, confirming that TSE significantly moderates the relationship between lead qualification skills and adaptive selling behavior.

Table 4. Moderation regression analysis

Predictor	Unstandardized Coefficient (b)	t-value	95% Confidence Interval
			Lower Limit
Constant	3.082	300.21***	6.601
Age	3.001	7.910***	2.981
Gender	0.051	0.086	–4.921
Education level	3.410	8.091***	3.412
Tenure with company	0.301	0.031	–2.181
Tenure in sector	0.081	0.032	–3.291
Lead Qualification Skills (LQS)	0.295	6.081***	0.621
Technology Self-Efficacy (TSE)	0.442	6.241***	4.510
LQS × TSE (Interaction)	0.214	2.302**	7.712
R^2	**0.321**		
F-statistic	**5.401* ****		

Note: N = 328. *p < 0.05, **p < 0.01, ***p > 0.001. Source: Primary data, 2024.

The findings indicate that salespersons with higher Technology Self-Efficacy (TSE) tend to exhibit greater Adaptive Selling Behaviour (ASB). The interaction between Lead-Qualification Skills (LQS) and TSE was statistically significant ($\beta = 0.214$, $t = 2.302$), demonstrating that TSE moderates the impact of LQS on ASB. This means that as TSE increases, the positive effect of LQS on ASB becomes stronger. Collectively, the model accounted for 32.1% of the variance in ASB and showed a statistically significant overall fit ($F = 5.401$), highlighting the combined importance of TSE and LQS in shaping adaptive selling outcomes.

The moderating effect is depicted in **Figure 2**, where the diverging lines represent different levels of TSE. Following Jose [48], the results support the hypothesis that higher TSE enhances the LQS-ASB relationship. The figure shows three levels of TSE—low, moderate, and high—and illustrates that ASB rises with increasing LQS across all levels. Importantly, the slope is steepest for salespersons with high TSE, indicating the greatest improvement in ASB as LQS develops, while those with moderate and low TSE show progressively smaller gains. This suggests that salespeople who are more confident in using technology can better leverage their lead-qualification skills to adjust their selling behaviour, emphasizing TSE's role in strengthening adaptive selling.

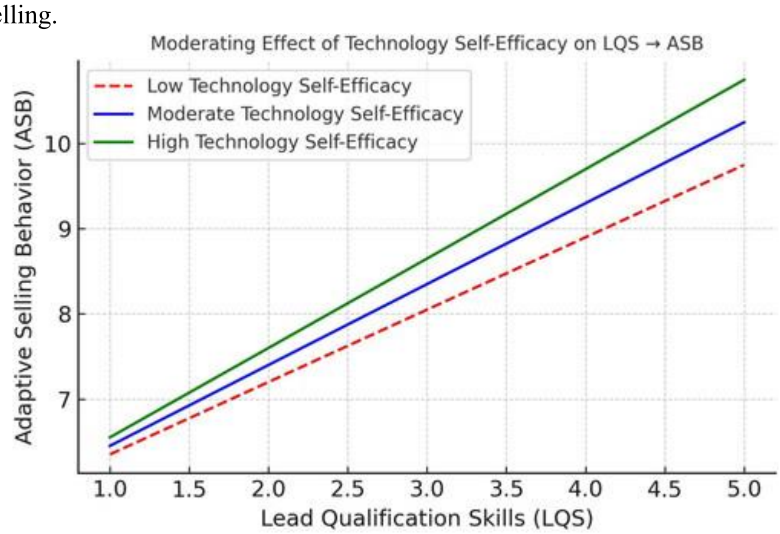

Figure 2. The moderating effect of salesperson's TSE

Moderating Role of Salesperson Technology Self-Efficacy (TSE)

Figure 2 demonstrates that TSE influences the strength of the relationship between Lead-Qualification Skills (LQS) and Adaptive Selling Behaviour (ASB). The non-parallel lines indicate a significant interaction effect. For salespersons with high TSE (represented by the green line), the slope is the steepest, showing that increases in LQS correspond to larger improvements in ASB. Conversely, for those with low TSE (red dashed line), the slope is more gradual, reflecting a weaker association between LQS and ASB. These results suggest that TSE amplifies the impact of LQS on adaptive selling performance, enhancing the effectiveness of lead-qualification skills in driving ASB.

Discussion

The results indicate that both Lead-Qualification Skills (LQS) and Technology Self-Efficacy (TSE) play important roles in enhancing salespersons' Adaptive Selling Behaviour (ASB), with TSE acting as a crucial moderator. Although the models accounted for a moderate 32.1% of the variance in ASB, this is typical in behavioral and social research, where multiple external and contextual factors influence outcomes [46, 49]. This suggests that while LQS and TSE are influential, additional unmeasured factors may also shape ASB, offering insights that extend current theory in emerging market contexts.

The positive relationship between LQS and ASB underscores the importance of effective lead qualification in enabling salespersons to customize their sales approaches according to client needs. This supports prior research [10, 11], highlighting that understanding customer requirements equips salespersons to respond flexibly in complex sales environments. Such adaptability is particularly relevant in markets like Uganda, where insurance awareness and uptake remain low [8]. In line with Adaptive Selling Behaviour Theory [17], these findings emphasize that tailoring sales strategies to situational and client-specific factors is critical, and strong LQS provides the necessary insights to achieve this.

The study also found a significant positive link between TSE and ASB, indicating that salespersons confident in their use of technology are better able to employ digital tools to support adaptive selling. This aligns with existing evidence that higher TSE enhances technology engagement, thereby improving sales adaptability [50, 51]. In technology-driven sales environments, such as Uganda's insurance sector, the ability to utilize digital platforms is essential for gathering client insights and delivering personalized solutions. The findings also resonate with the Technology Acceptance Model [21], which highlights that perceptions of usefulness and ease of use are critical in determining technology adoption. Salespersons with greater TSE are more likely to perceive digital tools as beneficial, allowing them to adapt their selling approach more effectively to client preferences.

Importantly, TSE was shown to moderate the relationship between LQS and ASB. Salespersons with higher technological confidence were better able to translate their lead-qualification skills into adaptive selling practices, consistent with the assertions of Román and Rodríguez [31]. Integrating technology into sales strategies not only improves client engagement but also supports more nuanced categorization and understanding of customer needs. Therefore, salespersons who are both skilled in lead qualification and confident in using technology exhibit the highest levels of ASB, highlighting the synergistic effect of TSE in enhancing adaptive selling performance.

Conclusion

This study underscores the important interplay between Lead-Qualification Skills (LQS), Technology Self-Efficacy (TSE), and Adaptive Selling Behaviour (ASB) among salespersons in Uganda's insurance industry. The results reveal that both LQS and TSE play significant roles in strengthening ASB, with TSE acting as a key moderator that enhances the positive impact of LQS on adaptive selling. By developing strong lead-qualification skills and cultivating confidence in technology use, insurance companies can better equip their sales teams to respond to the demands of a fast-changing market. Investing in targeted training and digital tools not only boosts individual sales effectiveness but also improves customer engagement and trust, offering a strategic approach to increasing insurance uptake in Uganda.

Implications

The findings of this study have important implications for managers, policymakers, and other stakeholders in Uganda's insurance sector, especially considering the industry's current growth opportunities and challenges.

Managerial implications

Insurance companies should prioritize training programs that enhance salespersons' Lead-Qualification Skills (LQS), enabling them to accurately evaluate potential clients and focus on high-value leads. Strengthening these skills can improve efficiency in prospecting and ultimately increase sales conversion rates.

Firms should also invest in developing technological competence among their sales teams through hands-on workshops, mentoring, and practical training on CRM platforms and other digital tools. Enhancing technology adoption can improve responsiveness to client needs and facilitate more efficient management of customer data.
Integrating technology-driven sales strategies, such as analytics and automation, can support faster and more precise customer insights, leading to better client retention and higher satisfaction levels.
Encouraging a culture of adaptability—through continuous training, fostering experimentation, and recognizing innovative practices—can stimulate employee-led innovations in sales processes, improving overall team performance and productivity.

Theoretical implications
This study contributes to theory by integrating Adaptive Selling Behaviour (ASB) Theory, Categorization Theory, and the Technology Acceptance Model (TAM). Categorization Theory provides a structured approach for grouping clients, which helps systematize adaptive selling and ensures consistency in customer interactions.
Incorporating TAM highlights the role of technology, such as CRM systems, in supporting adaptive selling. Technology facilitates real-time access to categorized customer data, enabling more precise and responsive sales strategies.

Policy implications
From a policy perspective, increasing insurance uptake in Uganda requires initiatives to enhance digital literacy and expand technology access for sales teams. Additionally, aligning educational and vocational programs with industry needs—particularly in areas related to LQS and ASB—can better prepare future sales professionals for a rapidly evolving marketplace.

Limitations and further areas for research

While this study offers important insights into the interplay between Lead-Qualification Skills (LQS), Technology Self-Efficacy (TSE), and Adaptive Selling Behaviour (ASB) in Uganda's insurance sector, several limitations should be acknowledged. The cross-sectional design restricts the ability to draw causal inferences among the variables, highlighting the need for longitudinal research to examine changes over time and better understand how LQS and TSE influence ASB dynamics.
The study's reliance on self-reported measures also raises the possibility of common method bias. Future research could address this by incorporating objective indicators such as customer feedback, sales performance metrics, or mixed-method approaches to triangulate data and improve validity.
Cultural factors may also shape how salespersons develop and apply LQS and TSE, suggesting the importance of cross-cultural investigations to explore contextual differences in adaptive selling practices. Furthermore, rapid technological advancements necessitate further exploration into how emerging tools and digital platforms impact LQS, TSE, and ASB, and how sales professionals can best leverage these innovations to remain effective.
Future studies could also examine the influence of organizational factors, including leadership styles and corporate culture, on the development of these competencies within sales teams. Comparative research across different industries or national contexts could provide insights into universal principles of adaptive selling, as well as sector-specific challenges, thereby informing more effective sales strategies and enhancing customer satisfaction in dynamic market environments.

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