The impact of assistant type, its past performance and task suitability for automation on the trust in automation in accounting

Abstract

The paper aims to examine whether an accountant's trust is impacted by the type of accounting assistant who processes the transaction (human vs. rule-based RPA vs. automation based on artificial intelligence), its past performance, and task suitability for automation. To achieve this goal, a 3x2 experimental design was proposed based on the three-layer model of trust (Hoff & Bashir, 2015). In varied experimental scenarios, 188 professional accountants from SMEs assessed their propensity to accept (without verification) journal entries processed by an assistant. The results show that trust in automation is higher for less complex tasks. While assistant past performance impacts trust regardless of task suitability for automation, assistant type plays a role only when the complex task is performed. In this case, accountants exhibit algorithm appreciation, trusting AI assistants more than humans. Nevertheless, none of the three types of assistants is seen as ideally reliable, necessitating accountants to use their subject matter expertise when supervising assistant's work. These results contribute to the literature on the use of automation by accountants in SMEs, algorithm aversion, task-technology fit, and factors impacting trust in automation. As respondents in this study come from one country (Poland), future research could focus on other cultural contexts.

Keywords: Trust, accounting information systems, experiment

1. Introduction

The global robotic process automation (RPA) market size was valued at almost USD 14 billion in 2023 and is projected to exceed USD 64 billion by 2032 (Fortune Business Insights, 2024). RPA implementation helps to improve business functions such as data entry and accounting and saves up to 50% of the cost of companies in European countries (Fortune Business Insights, 2024). Obviously, it is an alluring outcome for firms. However, from the accounting perspective, consuming the benefits of automation must not compromise the quality of accounting information. Automation introduced new pathways for error (Hoff & Bashir, 2015). On the one hand, overtrusting automation may result in poor accounting data quality. On the other hand, undertrusting automation does not allow for the optimal performance of accountants.

The success of integrating technology into organizations critically depends on users' trust in technology (Glikson & Woolley, 2020), and appropriate trust in automation is crucial to improving the efficiency of human-automation teams (Hoff & Bashir, 2015). Although it is expected that standardizing and automating accounting procedures leads to better accounting quality in terms of less error, improved efficiency, and time and cost savings (Cooper et al., 2019), automation could also hamper accounting quality by means of coding errors or malfunctions (C. Zhang et al., 2023). Additionally, automation is most suitable for highly standardized repetitive accounting tasks (Cooper et al., 2019) because bots, unlike humans, do not recognize when underlying processes change. This can lead to either the provision of incorrect data if overlooked or increased costs of monitoring and reconfiguring the bot (Eulerich et al., 2024). While adopting new technologies to assist an accountant's work may be beneficial, appropriate control over and trust in the assistant's work ensures high accounting data quality. Hence, understanding the factors that impact an accountant's trust in an assistant is vital to balance the benefits and the dark side of automation in accounting.

Based on the three-layer model of trust in automation (Hoff & Bashir, 2015) as an underlying theoretical framework, this research examines whether an accountant's trust changes depending on the type of accounting assistant that enters the transaction (human vs. rule-based RPA vs. automation based on artificial intelligence), its past performance and task suitability for automation. To establish causal relationships, the study employs a 3x2 experimental design with 188 experienced accounting professionals employed in small and medium accounting firms (SMEs). Focusing on SMEs is especially suitable when studying accountants' trust in automation because creating company-specific rules is a crucial stage in automating processes in accounting (Ala-Luopa et al., 2024). As tailoring a system to a specific company is costly, smaller firms may have limited possibilities given their budgets and cost/benefit trade-offs (Estep et al., 2024). Thus, SMEs are often forced to use generic automation, which is not fully adjusted to their specific needs, exposing them to a higher risk of error occurrences, which may result in false information provided by financial statements. In this setting, appropriate trust is critical to ensure correct accounting data.

The results confirm that accountants are not afraid of new technologies such as AI or RPA and may trust them more than humans acting as accounting assistants. Although accountants are open to the assistance of new technologies, they differentiate their trust in the assistant based on the accounting task performed by the assistant. Specifically, accountants exhibit higher trust in the case of less complicated, more repetitive tasks, which are more suitable for automation, while assistant type matters only when more complex tasks are performed. Moreover, accountants' trust depends on the assistant past performance, regardless of task difficulty and suitability for automation.

The study contributes to the literature in several ways. It gives empirical evidence on factors influencing the use of automation in accounting. Previous research on automation in the accounting domain is mainly qualitative, providing deep insight into the benefits and challenges of automation (Cooper et al., 2019; Eulerich et al., 2024; C. Zhang et al., 2023) and indicating factors impacting trust in automation (Ala-Luopa et al., 2024). This research confirms quantitatively on factors proposed by the three-layer model of trust (Hoff & Bashir, 2015). Our findings expand the knowledge of using automation in the accounting domain, focusing on SMEs. Few previous studies have investigated the use of automation in SMEs, mainly from auditors' perspectives. Estep et al. (2024) emphasize that the benefits of audit firms' investment in AI systems and the financial reporting quality of their clients may be compromised if the clients do not use AI. This is mainly the case for smaller companies, which implement technology at a slower rate than larger companies (Bakarich & O'Brien, 2021). Wiklund and Falland (2024) investigate the adoption of RPA in micro and small audit firms, identifying primary causes for non-adoption. Our study adds an important perspective on trust in automation from accounting professionals in SMEs, which must rely on generic automation due to limited resources.

The study also adds to the literature on task-technology fit. Previous research indicates characteristics of tasks most suitable for automation (Cooper et al., 2019; Kokina & Blanchette, 2019; Plattfaut & Borghoff, 2022). Our findings confirmed that task characteristics may explain the utilization of new technologies like RPA and AI in accounting. By investigating assistant type, the study contributes to the literature on algorithm aversion (Burton et al., 2020; Dietvorst et al., 2018; Mahmud et al., 2022). Although business professionals may exhibit algorithm aversion in some contexts, like auditing (Commerford et al., 2022) and data analytics (Chen et al., 2022), we found that accountants trust AI more than humans, suggesting algorithm appreciation.

The structure of the paper is as follows. The following section reviews the literature on trust and factors impacting trust in automation, with a particular focus on the use of automation in the accounting domain. The third section explains the experimental design of the study. The results and discussion are presented in the fourth section, while the latter section concludes the article.

2. Literature review and hypotheses development

2.1. Trust in automation

Trust may be defined as "an attitude that an agent will achieve an individual's goal in a situation characterized by uncertainty and vulnerability" (Lee & See, 2004; X. Zhang, Lee, Kim, & Hahn, 2023). With regard to trust in automation, conceptual models include i.a. a dynamic model of trust and reliance on automation (Lee & See, 2004), a three-layered trust model (Hoff & Bashir, 2015), and most recently, a four-concept framework of relational trust (Chiou & Lee, 2023). The current research uses Hoff and Bashir's model (2015) as the underlying conceptual framework most appropriate to the research focus.

Hoff and Bashir (2015) identify three layers of trust in automation: dispositional, situational, and learned, with different factors impacting each layer. Dispositional trust represents an individual's enduring tendency to trust automation (Hoff & Bashir, 2015). It reflects trust in other persons or machines upon the very first interaction, even if no prior interaction has occurred (Merritt & Ilgen, 2008). Thus, dispositional trust is relatively stable over time, and individuals with high levels of dispositional trust consistently trust others across situations, contexts, and individuals (Rose et al., 2010). The primary sources of variability in dispositional trust are culture, age, gender, and personality (Hoff & Bashir, 2015).

Situational trust relates to a specific context or situation, including both the external environment and the internal, context-dependent characteristics of the operator (Alsaid et al., 2023). Hoff and Bashir (2015) indicate that the type of system and its complexity, task difficulty, workload, perceived risk and benefits, organizational setting, and task framing are factors influencing external variability in situational trust. Internal factors that impact trust include self-confidence, subject matter expertise, mood, and attentional capacity.

According to Hoff and Bashir (2015), the third layer of trust is learned trust, which is directly influenced by the operator's preexisting knowledge (initial learned trust) and the automated system's performance (dynamic learned trust). Unlike dispositional and situational trust, learned trust is related to the characteristics of the automated system. Initial learned trust is shaped by the system's reputation and the operator's expectations, experience with similar technology, and understanding of the system. Dynamic learned trust varies during an interaction with a system. Thus, system performance with its reliability, validity, predictability, dependability, usefulness, type, timing, and difficulty of error influence this layer of trust.

Three layers of trust are related to different sources of variability in trust. In this research, we focus specifically on situational and learned trust to investigate factors impacting trust in automation in accounting, as both under- and overtrust are undesirable. Undertrust, i.e., a situation in which trust falls short of automation's capabilities (Lee & See, 2004), leads to the disuse of automated aid, which does not allow for the optimal performance of accountants and lowers the cost savings from automation. On the other hand, overtrust, i.e., placing too much trust in automation, leads to automation misuse (Hoff & Bashir, 2015; Lee & See, 2004). Consequently, overtrust errors go unnoticed (Aroyo et al., 2021), which results in reliance on incorrect data when preparing financial statements and making business decisions (Eulerich et al., 2024).

2.2. Task type

One of the factors influencing situational trust in automation is task difficulty (Hoff & Bashir, 2015). Trust in digital assistants depends highly on the task type that the assistant performs (X. Zhang & Lee, 2024), i.a. its complexity (So et al., 2024) and perceived objectivity (Castelo et al., 2019).

Automation is most suitable for highly standardized repetitive accounting tasks (Cooper et al., 2019). Rule-based, repetitive, less ambiguous tasks that are largely free of exceptions are most suitable for RPA (Bovaird et al., 2017). Drawing upon the theory of task-technology fit, Kokina and Blanchette (2019) add that high-volume processes using structured data are strong candidates for automation with RPA. According to Plattfaut and Borghoff (2022), it is even better if the process is already standardized prior to the application of RPA. However, in practice, caution is needed when assessing accounting tasks' suitability for automation. Korhonen et al. (2021) emphasize that when processes are assessed from a distance, the nonprogrammable accounting tasks can become misinterpreted as programmable, leading to faster, yet false, outcomes.

In this research, we investigate trust in the assistant in two high-volume accounting tasks with varying difficulty and complexity, i.e. processing journal entries for sales and purchases. Traditionally, journal entries are processed by a human accounting assistant and afterwards verified and posted by an accountant to the general ledger. Automation reduces human work by gathering necessary information, processing journal entries with account classification, and initial recording in the accounting systems. At this stage, if the automated assistant identifies a transaction with no recorded past history, an exception report is generated (Kokina & Blanchette, 2019) to be handled by an accountant. This does not guarantee that the automated assistant processes journal entries without mistakes in other cases, which in literature is often referred to as "missed alarms" (Hoff & Bashir, 2015; Langer et al., 2023; Parasuraman, 1997). In such cases, the automated assistant processes transactions with mistakes due to setup, which is inadequate for current business activities. As C. Zhang et al. (2023) state, automation, especially RPA, is prone to mistakes when business evolves and changes, and such changes make the current settings of automation obsolete. Therefore, it is crucial to remember that posting journal entries to the general ledger, thus using data processed by automation for financial reporting and decision-making, is an accountant's responsibility.

While preparing both journal sales and purchase entries is very common in everyday accountant's work, journal entries for sales are more standardized than journal entries for purchases and, thus, are more suitable for automation. We hypothesize what follows:

H1: The accountant’s propensity to accept (without verification) journal sales entries is higher than the propensity to accept (without verification) journal purchase entries.

In detail, journal sales entries can be limited to a certain number of categories the entity provides in its chart of accounts. In the case of journal purchase entries, not only does the type of purchase (e.g., service or materials) require appropriate classification in the accounts, but often also an assignment to the appropriate order, project or settlement over time is required. The above results in distinct accountants’ perceptions of task suitability (sales vs. purchase) for automation when preparing journal entries with sales transactions perceived as easier to standardize and thus treat automatically.

2.3. Assistant type

New technologies change the roles and tasks in the accounting profession, and it is expected that AI-based technology will replace human employees in routine tasks such as recording and collecting data (Ala-Luopa et al., 2024; Leitner-Hanetseder et al., 2021). Currently, accounting professionals are exploring the possibility of replacing some traditionally human tasks with automation in their everyday work, making trust in different types of assistants of particular importance.

Although automated algorithms often outperform human advice (Coleman et al., 2022), people often choose not to rely upon algorithmic decision aids while preferring human aid (Downen et al., 2024), a phenomenon known as “algorithm aversion” (Burton et al., 2020; Dietvorst et al., 2018; Mahmud et al., 2022). For example, Cvetkovic et al. (2024) find that people have higher trust in human assistants than AI assistants while having some control over the assistant's work increases trust in both human and AI assistants. In the financial profession, data analytics are perceived as less credible than human experts, but only when the advice suggests bad news (Chen et al., 2022). Algorithm aversion is observed in auditor judgments as well. Auditors receiving contradictory evidence from their firm's AI system (instead of a human specialist) propose smaller adjustments to management's complex estimates (Commerford et al., 2022).

Further, some research reveals contradictory findings suggesting algorithm appreciation when people choose AI suggestions more than those from humans (You et al., 2022) and directly self-report that they believe such recommendations more (Sharan & Romano, 2020). Most recently, accounting practitioners declared indifference regarding the assistant type until the outcomes were similar (Ala-Luopa et al., 2024). Moreover, managers do not view AI with aversion in a complex financial reporting setting (Estep et al., 2024). This may be partially because newer accounting professionals have grown up with technology, feeling more comfortable and less questioning its output (Harris et al., 2020).

Drawing on the literature, we hypothesize that accountants' trust in assistants differs between humans and automated assistants. Additionally, Hoff and Bashir (2015) argue that understanding the system impacts the initial learned trust, so the technology used to automate accounting tasks may shape user's trust. Rule-based automation (typical RPA) and automation based on artificial intelligence should be distinguished since AI is partially ambiguous (Plattfaut & Borghoff, 2022) and understanding how AI makes decisions could be impossible (Glikson & Woolley, 2020). The second hypothesis in this study is as follows:

H2: The assistant type impacts the accountant's propensity to accept (without verification) journal entries processed by a specific assistant.

Moreover, research advocates that the direction in which situational factors impact trust differs for complex and simple automation (Hoff & Bashir, 2015). Thus, the complexity of automation (RPA vs. AI) may interact with situational factors (task type and its suitability for automation). Research findings also suggest that relying on human vs. algorithmic advice depends on task difficulty, whereas subjects relied more on algorithmic advice as task difficulty increased (Bogert et al., 2021). Hence, we investigate the following hypotheses:

H2a: The assistant type impacts the accountant's propensity to accept (without verification) journal purchase entries processed by a specific assistant.

H2b: The assistant type impacts the accountant's propensity to accept (without verification) journal sales entries processed by a specific assistant.

2.4. Assistant past performance

Assistant performance is critical in formulating dynamic learned trust (Hoff & Bashir, 2015). One of the primary benefits expected from automating accounting tasks is eliminating errors (Cooper et al., 2019; Estep et al., 2024; Eulerich et al., 2022; Kokina & Blanchette, 2019). However, introducing automation has created new pathways for error (Hoff & Bashir, 2015) and can hamper accounting quality through coding errors or malfunctions (C. Zhang et al., 2023). Additionally, bots do not recognize when underlying processes change, which can lead to the provision of incorrect data (Eulerich et al., 2024).

Trust decreases after a trustee violates the trustor's expectations in both interpersonal (Elangovan et al., 2007; Lewicki & Brinsfield, 2017) and human-automation (Burton et al., 2020; X. Zhang & Lee, 2024) contexts. In turn, low-reliability automation declines trust and increases the extent to which the users monitor and verify automated advice (Gegoff et al., 2024). However, research in the accounting domain suggests accountants' tolerance towards potential automation failure (Ala-Luopa et al., 2024; Eulerich et al., 2024). Nevertheless, this early interview-based evidence needs to be confirmed, so we hypothesize that:

H3: The presence of errors in the past accounting periods lowers the accountant's propensity to accept (without verification) journal entries processed by a specific assistant.

Moreover, algorithm aversion literature suggests that the errors that are tolerable in humans become less tolerable when made by a machine (Dietvorst et al., 2015; Mahmud et al., 2022), so people may overreact to automation failures. Consequently, machine failures can lead to a more significant decline in trust compared to human trustees (Madhavan & Wiegmann, 2007; X. Zhang et al., 2023). Nevertheless, Langer et al. (2023) find contrary evidence suggesting that trust violation has a weaker effect on the automated system than on humans. This may be related to human error being perceived as random, whereas algorithmic error is systematic (Burton et al., 2020). Finally, results by Madhavan et al. (2006) indicated that trust dynamics differ not only for human vs. automation failures but also for task difficulty. Specifically, automation errors on less difficult tasks have a more significant negative impact on trust than errors on tasks perceived as more complex (Hoff & Bashir, 2015). We investigate these possibilities in two complementary hypotheses:

H3a: The presence of errors in the past accounting periods lowers the accountant's propensity to accept (without verification) journal purchase entries processed by a specific assistant.

H3b: The presence of errors made in the past accounting periods lowers the accountant's propensity to accept (without verification) journal sale entries processed by a specific assistant.

3. Experimental design

We employed an experimental design involving accounting professionals to test the hypothesized causal relationships. We conducted two (purchases and sales transactions) 3x2 experiments manipulating the type of accounting assistant processing journal entries and its past performance. The experiment resembles other experiments aimed at decision-making by accountants and managers (Asay et al., 2022; Bhaskar et al., 2019; Leuz, 2022). Participation in the study was voluntary, and no remuneration was offered to the participants. Participants were randomly assigned to six experimental groups.

Two independent variables encompassed in the 3 x 2 experimental design were (1) the type of accounting assistant (AI, RPA, human) and (2) past errors in invoice processing (small number of past errors present/absent). The subjects read a scenario that briefly described the solution implemented in the scope of sale/purchase transactions, characterized the type of accounting assistant, and outlined its past performance. Two groups of respondents were presented with an accounting information system (AIS) using AI or RPA. In contrast, the third group assumed to work in a company using AIS without automation, as journal entries were processed manually by accounting department employees. Further, each experimental group was provided information about the assistant's past performance, indicating that errors in the past occurred or did not occur. When errors in the past occurred, respondents were informed that they were of small amounts to investigate the impact on trust regardless of the impact of errors on financial information quality. The intent was to emphasize that the error is possible rather than draw attention to its materiality, which would become a major factor impacting accountants' decisions. This is because while the first impacts trust dynamics, the latter is strongly related to the AIS output. Past literature provided evidence for different effects of trust violation (like past error) on trust in automation vs people (Langer et al., 2023; Madhavan & Wiegmann, 2007; X. Zhang et al., 2023), which we want to confirm within accounting setting.

At the end of the scenario, respondents were asked to assess their propensity to accept (without verification) journal entries processed by the assistant. As each subject was asked to make the above-mentioned decision referring to purchase invoices and then the same decision referring to sales invoices, the dependent variable was measured twice. To examine the trust in the assistants, we propose the following extreme answers:

1 - I will not accept (without verification) any journal entry
10 - I will accept (without verification) all journal entries

Moreover, in the study, we asked four questions to check the understanding of the manipulations done in the experimental scenarios and three additional questions to investigate subjects' perception of risk associated with the use of AI, RPA or human journal entries in terms of the possibility to make improper accounts classification resulting in errors in the financial information.

From July to September 2024, a computer-assisted web survey using Survey Monkey software was conducted. The data gathered in the experiment were stored in MS Excel and uploaded into SPSS to perform the required tests. We used frequency, descriptive statistics, and nonparametric tests for statistical analysis. The significance threshold was set at .05.

4. Research results

We gathered 188 questionnaires from Polish accountants working in small and medium-sized entities. Based on answers to four manipulation checks verifying the cause-and-effect relationship between the scenario and the research outcome (Table 1) along with verification of respondents' declaration in the scope of accounting education and professional experience (Table 2), all answers were included in the database for statistical analysis.

Table 1. Manipulation check.

Manipulation check	N	Min	Max	Mode	Mean	SD
Any method of accounting for invoices, i.e. using artificial intelligence, robotic process automation, or employees, guarantees the correct accounting treatment of each purchase or sales invoice.	188	1	5	2	2.723	1.103
Automatically posted purchase or sales invoices may contain errors in the recognition of the appropriate accounts or errors regarding settlement (lack of settlement) over time.	188	1	5	4	3.963	0.921
The occurrence of errors in the posting of purchase or sales invoices in the past affects the decision to verify the correctness of invoices' postings in the current year by the person responsible for preparing the financial statements.	188	1	5	4	4.309	0.732
Accounting for purchase invoices is more complicated/complex than accounting for sales invoices.	188	1	5	5	4.160	0.905

Where: 1- definitely disagree, 2 – disagree, 3 – neither disagree nor agree, 4 – agree, 5 – definitely agree.

The demographic data of 188 participants are presented in Table 2.

Table 2. Respondents' demographic data.

	Frequency	Percentage		Frequency	Percentage
Professional experience			**Years of professional experience**		
I have already worked / I am currently working in the accounting department	188	100.0	Up to 4 years	3	1.6
I have no experience in the accounting department, but I have experience working in the financial/economic finance department	0	0.0	From 5 to 10 years	28	14.9
I have no experience in the accounting department	0	0.0	Above 10 years	157	83.5
Size of entity the respondent gained his/her experience			**Occupied position**		
0-10 employees (micro-enterprise)	56	29.8	Lower-level employee	0	0.0
>10-50 employees (small enterprise)	95	50.5	Middle-level employee	12	6.4
>50-250 employees (medium enterprise)	37	19.7	Middle management employee	53	28.2
			Top management, owner	123	65.4
Gender of respondents			**Education**		
Female	154	81.9	Elementary	8	4.2
Male	34	18.1	High school	143	76.1
			College/university	37	19.7

Most respondents were women (81.9%) occupying top-management positions (65.4%), mainly in small entities (50.5%). Since it was required for the subject to have at least 3 years of experience in accounting, an average experience was almost 19 years (18.6). We aimed for respondents with more than 3 years of professional experience as those have gained experience working with AIS and possibly with different types of automation and have a higher chance to already be at least partially responsible for making accounting decisions regarding financial reporting.

To start with the verification of the hypotheses stated in our study, we analyzed gathered data with descriptive statistics (Table 3). Indicating "1," respondents made the decision to verify all journal entries processed by AI, RPA or a human. In other words, by choosing “1,” they showed distrust with the assistant; while indicating “10”, they showed trust in automation or employees processing journal purchase/sales entries.

Table 3. Mean accountants’ propensity to accept (without verification) journal purchase/sales entries.

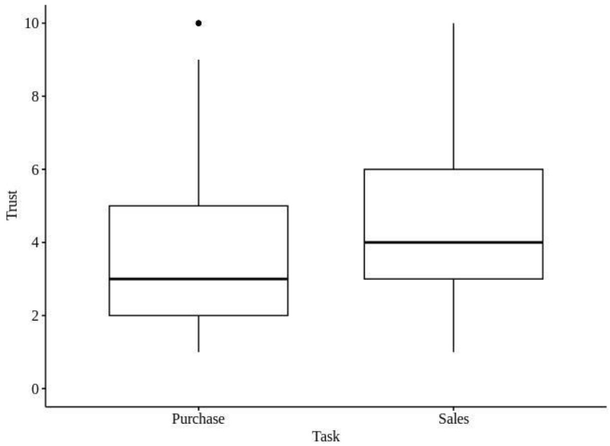
Journal purchase entries			
	Error		**TOTALS**
	Present (Y)	Absent (N)	
Type of AIS assistant	Median/Mean/SD/N	Median/Mean/SD/ N	Median/Mean/SD/N
Artificial intelligence (AI)	3.000 / 4.000 / 2.194 / 33	4.000 / 4.500 / 2.110 / 32	4.000 / 4.246 / 2.151 / 66
Robotic process automation (RPA)	3.000 / 2.742 / 1.731 / 31	4.000 / 4.129 / 1.784 / 31	3.000 / 3.435 / 1.878 / 62
Accounting department employee (H)	1.000 / 2.452 / 2.528 / 31	4.000 / 3.667 / 1.583 / 30	3.000 / 3.049 / 2.187 / 61
TOTALS	3.000 / 3.084 / 2.258 / 95	4.000 / 4.108 / 1.856 / 93	3.000 / 3.598 / 2.123 / 188
Journal sales entries			
	Error		**TOTALS**
	Present (Y)	Absent (N)	
Type of AIS assistant	Median/Mean/SD/N	Median/Mean/SD/ N	Median/Mean/SD/N
Artificial intelligence (AI)	4.000 / 4.152 / 1.349 / 33	5.000 / 5.250 / 2.125 / 32	5.000 / 4.692 / 1.845 / 65

Robotic process automation (RPA)	4.000 / 4.032 / 2.536 / 31	5.000 / 4.452 / 1.823 / 31	4.000 / 4.242 / 2.200 / 62
Accounting department employee (H)	2.000 / 3.742 / 3.055 / 31	4. 000/ 3.667 / 1.583 / 30	4.000 / 3.984 / 2.526 / 61
TOTALS	4.000 / 3.979 / 2.383 / 95	5.000 / 4.656 / 1.970 / 93	4.000 / 4.312 / 2.203 / 188

Where: "1" - I will not accept (without verification) any journal entry. "10" - I will accept (without verification) all journal entries.

Descriptive statistics for journal sales/purchase entries, together with the Wilcoxon signed-rank test for paired samples (z= -4.808; $p < 0.001$), show the significant difference between the propensity to accept (without verification) the journal entries for purchases and sales (Figure 1). The median score on purchases was 3.0 compared with 4.0 on sales, which indicates that respondents were more willing to accept (without verification) journal entries for sales.

Figure 1. Propensity to accept (without verification) journal entries for purchases and sales



Where: "1" - I will not accept (without verification) any journal entry. "10" - I will accept (without verification) all journal entries.

Figure 1 indicates that when respondents read the scenario about the journal purchase entries, they were less prone to accept (without verification) journal entries than when they decided about journal sales entries, no matter whether they were assigned to the experimental scenario with AI, RPA, or employees hired in the accounting department and no matter whether they were informed about the presence or absence of errors in the past accounting periods. This result confirms H1, stating that accountants are more likely to accept (without verification) journal sales entries.

To determine whether there were any statistically significant differences between the six experimental groups, we conducted the nonparametric Kruskall-Wallis test, as our data did not meet the normal distribution assumption for one-way ANOVA (although tests run with ANOVA confirm the results presented below). The dependent variable was each respondent's propensity to accept (without verification) journal entries processed by automated AIS (AI, RPA) or accounting department employees and in the presence or absence of errors in the prior accounting periods.

Table 4. Kruskal-Wallis tests

Journal purchase entries

Factor	Statistic	df	p	Rank ε^2	95% CI for Rank ε^2 Lower	Upper
Assistant type	12.349	2	0.002	0.066	0.019	0.149
Error P/A	18.607	1	<.001	0.100	0.034	0.200

Journal sales entries

Factor	Statistic	df	p	Rank ε^2	95% CI for Rank ε^2 Lower	Upper
Assistant type	4.124	2	0.127	0.022	0.002	0.090
Error P/A	5.605	1	0.018	0.030	0.002	0.091

Note. Tests are conducted separately for each variable without accounting for multivariate effects.

Table 5. Dunn's post-hoc comparisons.

Journal purchase entries

Comparison	z	W_i	W_j	r_{rb}	p	p_{bonf}	p_{holm}
AI - RPA	2.056	111.800	92.202	0.226	0.040 *	0.119	0.079
AI - H	3.490	111.800	78.402	0.338	< .001 ***	0.001 **	0.001 **
RPA - H	1.425	92.202	78.402	0.165	0.154	0.462	0.154
P - A	-4.314	77.789	111.570	0.359	< .001 ***	<.001 ***	<.001 ***

* p < .05, ** p < .01, *** p < .001

Journal sales entries

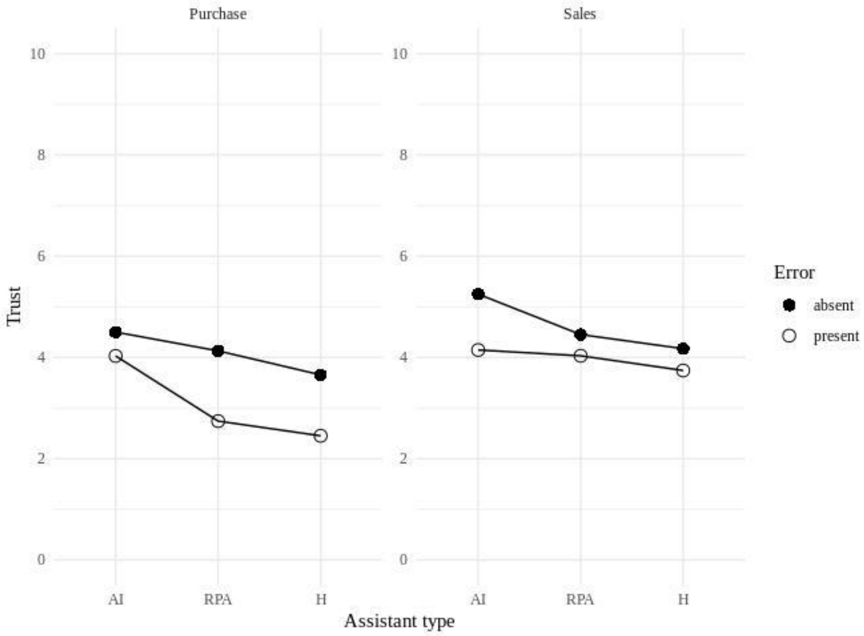
Comparison	z	W_i	W_j	r_{rb}	p	p_{bonf}	p_{holm}
AI - RPA	1.414	105.062	91.548	0.158	0.157	0.472	0.314
AI - H	1.961	105.062	86.246	0.185	0.050*	0.150	0.150
RPA - H	0.546	91.548	86.246	0.072	0.585	1.000	0.585
P - A	-2.368	85.305	103.892	0.198	0.018 *	0.18 *	0.018 *

* p < .05, ** p < .01, *** p < .001

Rank-biserial correlation based on individual Mann-Whitney tests.

The results presented in Tables 4 and 5 confirm that there is a significant difference in accepting (without verification) the journal purchase entries across three groups of AIS assistant type [(2, N=188) = 12.349, p = 0.002], as well as among the scenarios with past error present or absent [(1, N = 188) = 18.607, p = < 0.001]. Respondents were more willing to accept (without verification) journal entries already processed by artificial intelligence than when processed by accounting employees, despite errors present or absent in prior accounting periods (Figure 2). This confirms **H2a**, assuming the type of accounting assistant impacts the decision to accept (without verification) processed journal purchase entries. Further, in the case of journal purchase entries, hypothesis **H3a** was confirmed as respondents showed a lower willingness to accept (without verification) already processed journal purchase entries when errors were present in prior accounting periods. With these results, it can be stated that, regarding journal purchase entries, both main effects were confirmed.

Figure 2. Propensity to accept (without verification) the purchase/sales journal entries in a 3 x 2 experimental



design.
Where: “1” - I will not accept (without verification) any journal entry. “10” - I will accept (without verification) all journal entries.

The results presented in Tables 4 and 5 confirm that only one main effect was confirmed regarding journal sales entries. The presence or absence of error in the past accounting periods affected the decisions made by the accountants [(1, N = 188) = 5.605, p = 0.018]. Respondents who were provided with the scenario indicating that there were a few errors in the past were less willing to accept (without verification) the journal entries processed by an assistant regardless of its type. However, no statistical significance was found about the type of accounting assistant in the case of journal sales entries [(2, N = 188) = 4.124, p = 0.127]. With these results, it can be stated that hypothesis **H2b** was rejected, while **H3b** was confirmed.

5. Discussion

Our research confirmed that trust in automation depends on task suitability for automation. This is in line with Hoff and Bashir's (2015) suggestion that situational trust in automation depends on task difficulty and results obtained by So et al. (2024) on the role of task complexity in trust formation. Accountants were more willing to accept (without verification) journal sales entries that are more repetitive and largely free from exemptions in comparison with journal purchase entries. It confirms prior research results in which Bovaird et al. (2017) characterized less ambiguous tasks as the most suitable for RPA. Of the two types of transactions that most often occur in companies and that we selected for our study, sales transactions are easier to automate. With this finding, we add to the research stream based on the theory of task-technology fit, as we incorporated very specific users' tasks requiring specific functionalities of the technology used for processing journal entries. In the scope of AIS, we confirmed that task characteristics may explain the utilization of new technologies like automation (in the form of RPA or AI) in accounting.

With regard to assistant type, our results show a significant difference in how accountants trust in humans vs AI in favor of AI, but only when performing complex tasks. These findings contradict the prior findings on algorithm aversion by Downen et al. (2024) and Cvetkovic et al. (2024), who found that people have higher trust in human assistants than in AI assistants. Instead, our research adds to the literature on algorithm appreciation (You et al., 2022), also confirming that accountants are convinced of AI in a complex financial reporting setting (Estep et al., 2024). Interestingly, accountants trust somewhat ambiguous AI more than in easier-to-understand rule-based RPA, showing a tendency to assign positive evaluations to unfamiliar objects (Madhavan & Wiegmann, 2007). This confirms system understanding as a factor shaping initial learned trust. At the same time, algorithm appreciation is not visible regarding less complex accounting tasks. Thus, in line with Hoff and Bashir (2015), we argue that task difficulty influences accountants' trust as a situational factor.

We also confirmed that the assistant's past performance impacts an accountant's dynamic learned trust, regardless of the situational factor in the form of task difficulty. Specifically, our results confirm that trust violation, like error occurrences in the past, lowers the trust towards the assistant. However, the effect of trust violation is not the same for human and automated assistants (Madhavan & Wiegmann, 2007) and may interact with task difficulty (Madhavan et al., 2006).

The respondents in our study indicated that none of the three types of assistants (AI, RPA, human) guarantees the correct processing of each journal entry. Moreover, they are aware that automatically posted invoices may contain errors in recognition of the appropriate accounts or errors regarding settlement (lack of settlement) over time. Notably, accountants regard automation as not always reducing the possibility of making errors, noting that automation opens new pathways for error (Hoff & Bashir, 2015) and can hamper accounting quality through coding errors or malfunctions (C. Zhang et al., 2023). Fortunately, accountants do not entirely rely on the assistants, mobilizing their subject matter expertise when supervising the assistant's work.

Finally, our research suggests that accountants have limited trust in automation (AI and RPA) and human assistance, which could otherwise pose a risk of unnoticed errors or misuse of automation (Aroyo et al., 2021; Eulerich et al., 2024). The relatively high level of trust in AI, compared to other accounting assistants studied, is a positive indicator of the potential benefits of using AI in accounting.

6. Conclusions

The aim of this research was to investigate the impact of accounting assistant type, past performance, and task suitability for automation on accountants' trust in assistant. Based on the three-layer model of trust in automation (Hoff & Bashir, 2015) as an underlying theoretical framework, we employed a 3x2 experimental design with 188 experienced accounting professionals in small and medium accounting firms (SMEs).

The results of our study clearly show that nowadays, accountants are not afraid of new technologies such as AI or RPA and may trust them more than humans acting as accounting assistants. Although accountants are open to the assistance of new technologies, they differentiate their trust in the assistant based on the accounting task performed by the assistant. Specifically, accountants exhibit lower trust in the case of more complicated, less repetitive tasks. We also found that accountants' trust depends on the assistant past performance, regardless of task difficulty and suitability for automation. Finally, the assistant type impacts trust only when a more difficult task is performed. These findings contribute to several streams of literature, especially on the use of automation by accountants in SMEs, algorithm aversion, task-technology fit, and factors impacting trust in automation.

The study has several limitations. Firstly, the respondents were gathered from one country. However, Poland is one of the leading countries in terms of digitalization, especially in taxation (Deloitte, 2023), which forces Polish accountants to implement new technologies in AIS due to the strict link between accounting and taxation. Another limitation is derived from the experimental method, which simplifies the complex world of actual business operations, allowing for the isolation of selected factors under investigation. Finally, our study is limited to the perspective of SME accountants, whose behavior may differ from that of large entities using more sophisticated software for accounting purposes.

Since trust is context-dependent and varies across cultures (Aroyo et al., 2021), future research could investigate accountants' trust in different cultural and digitalization contexts to compare results and applicability. Experiments applying different factors and their possible interaction with factors identified in this paper could also contribute to understanding trust dynamics in the accounting domain. Particular interest should be placed on different kinds of errors and system malfunctions that may occur while using automation in AIS. We also suggest considering the application of varying experiment types, i.e. natural, field or quasi-experiment.

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