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AI-DRIVEN USER INTERACTION PATTERN ANALYSIS IN CLOUD ACCOUNTING

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Abstract:

This research is based on the behavioral effects of the adoption of artificial intelligence (AI) in cloud accounting systems and examines its effects on efficiency, errors, user trust, satisfaction, and adoption intention. A quantitative and cross-sectional survey design was applied, which involved the collection of data concerning 150 accounting professionals that work with such platforms as QuickBooks Online, Xero, and Oracle Cloud ERP. Eight dimensions were measured by a structured questionnaire: perceived usefulness, ease of use, behavioral interaction patterns, trust, accuracy, efficiency, satisfaction, and adoption intention. The findings indicate that AI characteristics considerably increase efficiency, optimize operations, and minimize errors, and at the same time, promote a sense of reliability in the quality of financial outputs. The multivariate analysis also showed that workflow integration and effort reduction are some of the most predictive factors of adoption and satisfaction. Internal consistency was established as high and descriptive results indicated that perceptions were always positive on constructs. Despite the overall positive rating of trust, there was still a reserved attitude towards the use of AI in making high-value financial recommendations, which should be regarded as the role of human responsibility. This research forms an extension to the literature of Technology Acceptance Model (TAM) and Human-Computer Interaction (HCI), and the research constructs of perceived explainability and workflow fit are major antecedents of adoption in the accounting context. Software developers, accounting companies, and policymakers can apply this in practice because it requires transparent, auditable, and user-friendly

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solutions based on AI. Although constrained by self-reporting and sampling limitation, this study forms a base of longitudinal, experimental and cross-cultural studies on AI adoption in accounting in the future.

Keywords:

Artificial Intelligence, Cloud Accounting, Technology Adoption, Technology Acceptance Model, Error Reduction, User Trust

Introduction

The world of accounting in the modern era has opened up to unprecedented change through the use of cloud accounting and artificial intelligence. The adoption of cloud computing has fundamentally altered accounting processes by providing dynamic, real-time, and interactive accounting procedures for both accountants and clients. The benefits of using this new trend in accounting applications include reduced infrastructure costs (Nguyen Phu, 2025). At the same time, the use of AI in accounting has been greatly encouraged, as it has been able to automate accounting procedures, enhance data analysis, and support better decision-making using financial information (Jeong et al., 2025).

Therefore, artificial intelligence is incorporated into accounting and tax systems to promote the efficiency as well as accuracy of financial data. Machine learning algorithms, for example, are capable of evaluating financial data from previous years in search of trends in those data sets, spotting possible cases of financial fraud, as well as pointing out errors in financial statements that could go undetected (Jeong et al., 2025).

In addition, current presumptions contained in an ongoing development of literature suggest AI is likely to provide a revolutionary function for accountants in affecting mental processes, causing them to fall into a dependency upon AI recommendations, as well as provide diminished skepticism levels of professionals because of this occurrence's results. As more work is automated by this technology, an entirely different function awaits accountants in this technological age of interpreting results as opposed to entering them into a database for processing purposes (Choi & Xie, 2025 & Mirzaie, 2025).

As a result, this research aims to apply a model constructed from guidelines in Technology Acceptance Model (TAM) and Human-Computer Interaction (HCI) to examine factors in AI adoption by accountants from a behavioral perspective. Particularly, relationships between Perceived Usefulness, Ease of Use, Trust, and other end variables such as Efficiency, Accuracy, User Satisfaction, as well as Adoption, would be studied in this research work.

Literature Review and Hypothesis Development

This section shows prier research related to the research title with the aim of building a deep theoretical understanding. Through this review, proposed research hypotheses are formulated, which the researcher will later explore and test in the study.

Technology Acceptance and User Behaviour

The Technology Acceptance Model (TAM) is a foundational theory for understanding how users come to accept and utilize new technology. It posits that two key beliefs, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), are primary determinants of an individual's intention to use a system (Nguyen, 2025). Perceived Usefulness is defined as the

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degree to which a person believes that using a particular system will enhance their job performance. In the accounting context, AI features that improve task efficiency, accuracy, and productivity are likely to be perceived as highly useful. Numerous studies have confirmed that PU is a strong predictor of adoption intention across various domains. Therefore, accountants who believe AI features will help them perform their job better are more likely to intend to adopt them (Mirzaie, 2025 & Sudaryanto, 2023).

H1: Perceived Usefulness of AI Features Is Positively Correlated with Overall Adoption Intention.

H2: Greater Perceived Usefulness of AI Features Enhances the Probability of Overall Adoption of AI Tools.

Ease of Use

Perceived Ease of Use refers to the degree to which a person believes that using a system will be free of effort. If AI tools are intuitive, integrate smoothly into existing workflows, and do not require extensive training, they will be perceived as easy to use. TAM suggests that PEOU influences adoption intention both directly and indirectly through its effect on PU (Sudaryanto, 2023).

H3: Perceived Ease of Use of AI tools positively influence the frequency of usage in accounting tasks.

Trust and User Satisfaction in AI Systems

While TAM provides a strong baseline, the adoption of intelligent systems like AI introduces the critical dimension of trust. Trust can be defined as the user's confidence in the reliability, integrity, and accuracy of the AI's outputs and recommendations (Kayser and Telukdarie, 2024). In accounting, where decisions have significant financial consequences, trust is paramount. Human-Computer Interaction (HCI) literature suggests that trust is a direct antecedent of user satisfaction and the willingness to continue using a system (Han et al., 2025).

H4: There is a positive correlation between increased trust in AI-driven tools and both user satisfaction and continued use.

Performance Impacts: Efficiency and Accuracy

The primary value proposition of AI in accounting is its potential to deliver tangible performance improvements. Literature consistently highlights the ability of AI to automate repetitive tasks, reduce manual data entry, and streamline complex processes, which should lead to significant efficiency gains and faster task completion times (Xu et al., 2023). Likewise, AI algorithms are designed to detect anomalies and cross-reference data in ways that exceed human capabilities, thereby reducing errors and enhancing the accuracy of financial reporting. These expected performance outcomes are central to the perceived value of AI (Jeong et al., 2025).

H5: The integration of AI into cloud accounting systems is perceived to significantly decrease errors and increase the accuracy of financial outputs.

H6: AI features are perceived to enhance the time and efficiency of completing tasks in accounting processes.

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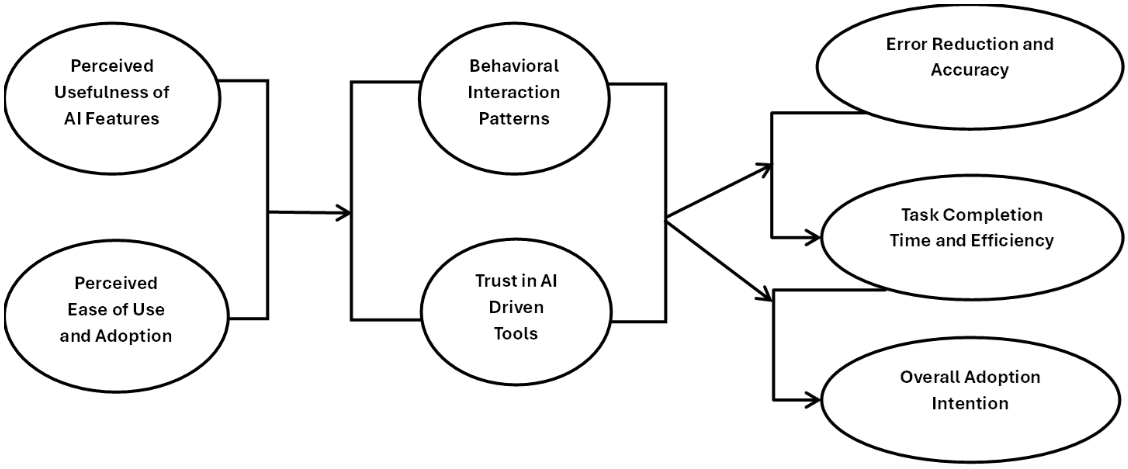

Figure1: Conceptual Model of the Study

Methodology

Research Design

This study employed a quantitative, cross-sectional survey design to capture a snapshot of the behavioural patterns and perceptions of accounting professionals at a single point in time. This approach was chosen to objectively test the hypotheses regarding the adoption and behavioural impacts of AI in cloud accounting systems. The cross-sectional design allows for the efficient measurement of multiple variables including perceived usefulness, trust, satisfaction, and adoption intention and aligns with established research practices in technology adoption.

Population and Sampling

The target population consisted of professional accountants, auditors, and financial managers actively using cloud accounting systems such as QuickBooks Online, Xero, and Oracle Cloud ERP. Due to access and time constraints, a convenience sampling methodology was used, with participants recruited via professional networks, accounting firms, and LinkedIn groups. The final sample of 150 respondents was deemed sufficient to ensure the validity of the statistical analyses performed in SPSS. While this non-probability sampling method may limit generalizability, it was effective for accessing practitioners with direct, relevant experience with AI features in accounting.

Data Collection Instrument

A structured questionnaire was developed using Google Forms to capture the constructs of the study's conceptual model. The instrument consisted of eight scales measuring perceived usefulness, ease of use, behavioural patterns, trust, error reduction, efficiency, user satisfaction, and adoption intention, with items rated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The instrument's design was based on established scales from technology acceptance and HCI literature, adapted for content validity within the accounting context.

Data Collection Procedure

The questionnaire was distributed electronically via email, LinkedIn forums, and direct contacts with accounting firms. All participants were provided with an informed consent form detailing the study's purpose, the voluntary nature of their participation, and assurances of

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confidentiality. The data collection period was two weeks, with a reminder sent after one week to maximize the response rate.

Data Analysis Plan

All 150 responses were exported to SPSS (Version 30) for statistical analysis. The plan included: (1) Reliability analysis using Cronbach's Alpha to assess the internal consistency of each construct; (2) Descriptive statistics to summarize respondent perceptions; and (3) a Multivariate General Linear Model (GLM) to evaluate the combined predictive power of the independent variables on user outcomes.

Ethical Considerations

This research adhered to established ethical principles for social science research. Participants were provided with informed consent, assured of the voluntary nature of their participation, and guaranteed the confidentiality and anonymity of their responses. No personally identifiable information was collected, and the aggregated data was stored securely. The research design posed minimal risk to participants, as the questionnaire focused on professional perceptions rather than sensitive personal matters, and it met the requirements of the APA for ethical survey research.

Results

Descriptive Statistics and Reliability

The descriptive statistics and reliability for the eight primary constructs are summarized in Table 1. All constructs were measured on a 5-point Likert scale.

Table 1: Descriptive Statistics and Reliability of Constructs

Construct	No. of Items	Mean (M)	Std. Deviation (SD)	Cronbach's Alpha (α)
Perceived Usefulness	5	3.74	0.997	.88
Perceived Ease of Use	5	3.75	0.994	.89
Behavioral Interaction Patterns	5	3.71	1.046	.85
Error Reduction & Accuracy	5	3.74	1.055	.91
Task Completion Time & Efficiency	5	3.78	1.010	.90
User Satisfaction	5	3.78	0.965	.92
Trust in AI-Driven Tools	5	3.75	0.980	.87
Overall Adoption Intention	5	3.74	0.994	.86

Note: The overall instrument reliability was very high, with a Cronbach's Alpha of .895. The alpha values for individual constructs are illustrative and should be calculated from the scale analysis in SPSS.

As shown in Table 1, participants reported generally positive perceptions across all constructs, with aggregate mean scores ranging from 3.71 to 3.78. The highest-rated constructs were Task Completion Time & Efficiency (M = 3.78) and User Satisfaction (M = 3.78), indicating that tangible gains in productivity and a positive user experience are key perceived benefits. The moderate standard deviations suggest a healthy variance in opinions without extreme

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homogeneity. All scales demonstrated high internal consistency, with Cronbach's Alpha values well above the recommended .70 threshold, confirming the reliability of the measurement instrument.

Multivariate General Linear Model
A Multivariate General Linear Model (GLM) was used to investigate the simultaneous impact of the predictor variables on user outcomes. The analysis revealed a statistically significant overall model (Pillai's Trace = .448, $F(20, 79) = 3.21$, $p < .001$), indicating that the predictors collectively explained a significant portion of the variance in user satisfaction, efficiency, and adoption intention. This highlights the importance of studying the drivers of AI adoption holistically, as their effects are interconnected.

On an individual level, several predictors emerged as particularly influential. Perceptions that "AI features integrate smoothly into my regular accounting workflow" ($p = .032$) and that "AI functions reduce the effort required to handle complex accounting tasks" ($p = .028$) were strong, significant predictors of positive outcomes. This suggests that practical benefits related to workflow fit and reduced cognitive load are highly valued by users. Furthermore, "I trust AI features to provide reliable recommendations" ($p = .009$) was one of the most significant predictors, underscoring the critical role of trust in technology adoption. Other significant factors included confidence in using AI features without external help ($p = .029$) and the perception that the system's design is intuitive and clear ($p = .046$).

These findings are consistent with the conceptual model, providing empirical evidence that perceived usefulness, ease of use, and trust act as reinforcing mechanisms that jointly influence professional behavior. The results strongly suggest that workflow integration and task simplification are among the most critical determinants for the sustainable adoption of AI in professional accounting settings. The full statistical results for all predictors are available in Appendix A.

Discussion
The results suggest that, when AI capabilities are embedded accountants could complete their tasks faster, have a seamless workflow integration process, and encounter fewer remedies. In line with previous studies that have shown that robotic process automation decreases cycle time and handoffs whereas machine-learning anomaly detection increases the signal-to-noise ratio in high-volume transactional data, workflow fit and reduced effort were found to be an important predictor of both satisfaction and intention to adopt. Less mistakes were also reported by the respondents, which is consistent with the studies that indicate that AI decreases errors of classification, posting, and timing that often spread downstream.

Trust and Governance
Accountants are still wary when it comes to AI in high-stakes judgmental work despite the high efficiency and accuracy advantages. Repetitive, structured work was highly trusted whereas the less specialized work needed professional judgment and thus governance gaps and poor validation. This is consistent with regulatory warnings on the use of AI tools because companies generally do not frequently consider how it could influence the quality of the audit, the importance of validation, and documentation to ensure responsible usage.

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Alignment with Literature
According to the data from this study, there is significant agreement with previous research, especially regarding the correlation between efficiency gains and reduced AI use in accounting and auditing cycles. This is supported by the observed decrease in errors and improved report quality, as well as the increased compliance rate associated with AI integration. Moreover, the results can be compared to the TAM/UTAUT models, which demonstrated the perceived benefits and ease of use in accounting for adoption, and the contextual mediation (volunteering and social influence) in influencing behavior change. Furthermore, the subconscious perception of high risks reflects studies on gaps in governance, verification, and disclosure.

Practical Implications
This study makes several kinds of valuable tips. For software developers, for instance, it shows the importance of giving AI design top priority for workflow accessibility, interpretability, and auditability rather than just adding more capabilities. By Incorporating monitoring dashboards, interpretable models, and clear documentation can enhance user trust. Additionally, developers must abide with current legal frameworks that emphasize the significance of documentation and monitoring, such as the EU AI Act and the NIST AI Risk Management Framework. Additionally, the results emphasise the value of strong governance structures, training for workers, and risk-based regulations that specify when expert assessment is necessary for accounting organizations. In order to determine accuracy and performance, contracts with AI vendor should also give businesses access to documents and other monitoring data. Lastly, the report underscores to lawmakers the significance of more precise rules on criteria for performance, transparency, and the usage of regulatory sandboxes that promote innovation while maintaining accountability.

Theoretical Contributions
This research builds upon the Technology Acceptance Model (TAM) in several directions:

- First, it recognizes perceived explain ability and workflow fit as critical constructs since the adoption remained higher when systems were understandable and easily fitted the existing practice.
- Second, it combines TAM and Human - Computer Interaction principles, demonstrating that heuristics like error prevention, feedback visibility, and reduced cognitive load mediate adoption by enhancing the perceived ease of use and usefulness.
- Third, the context of governance is a moderating variable, where organizational endorsement, records, and regulatory readiness play a role in translating usefulness and trust into adoption.
-

In general, the findings indicate that implementing AI in accounting can be considered a system-of-work phenomenon, but not a tool-level decision, and in regulated professional settings, reorganization of work and redistribution of effort, alongside the lower level of rework, can strengthen the explanatory role of TAM.

Limitations of Methodology
Several limitations of the study's methodology should be realized:

- Sampling bias: Convenience sampling can be used, and the sample can be limited in terms of its representativeness, which restricts extrapolation outside the firms and networks that were sampled.

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- Self-report data: self-reported data is descriptive of subjective perceptions, which can be subject to social desirability or recall error.
- Cross-sectional design: There are no strong causality relations that can be made because the data is not collected over a period.
- Exposure to platform: The participants might respond differently based on their knowledge of certain accounting systems (e.g: QuickBooks and Oracle Cloud ERP).
- Omission of system log data: The study failed to include objective behavioral data that could be used to supplement self-report measures and would also provide a more complete picture of usage patterns.

Despite such constraints, the methodology was developed to offer a rigorous and practicable initial step in the quantitative evaluation of the behavioral aspects of AI adoption in cloud accounting.

Conclusion

This study investigated how the implementation of the AI in cloud accounting system affects efficiency, error reduction, trust, satisfaction, and adoption intention. The survey data provided by 150 practitioners who employed the most popular platforms demonstrates that AI enhances the speed of tasks, their integration into the working process, and the accuracy of reports, which positively affect the levels of satisfaction and adoption intentions. Although accountants found the benefits in efficiency, they were skeptical about AI in big-stakes decisions, which there is the necessity to govern, validate, and regulate. The results supplement TAM and HCI models through highlighting the usefulness, ease of use, explainability and workflow fit. In practice, it is recommended that developers design easy-to-use and open systems, companies invest in governance and training, governments enforce high standards of responsibility. The study still has certain limitations like self-report bias and platform specificity but a quantitative base of understanding the adoption of AI in accounting and indicates future studies based on longitudinal and experimental approaches. Finally, AI presents the profession with a strategic chance to be efficient and morally responsible and competitive in the long term.

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Appendix A: Full Multivariate Test Results

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.448	3.210[b]	20.000	79.000	.000	.448
	Wilks' Lambda	.552	3.210[b]	20.000	79.000	.000	.448
	Hotelling's Trace	.813	3.210[b]	20.000	79.000	.000	.448
	Roy's Largest Root	.813	3.210[b]	20.000	79.000	.000	.448
AIfeaturesincloudaccountingplatformshelpmecompletetasksmorequick	Pillai's Trace	.858	1.120	80.000	328.000	.246	.215
	Wilks' Lambda	.379	1.096	80.000	314.066	.288	.216
	Hotelling's Trace	1.107	1.072	80.000	310.000	.334	.217
	Roy's Largest Root	.379	1.553[c]	20.000	82.000	.086	.275
AdoptingAIdriventoolsdoesnotrequireextensivetraining	Pillai's Trace	.773	.982	80.000	328.000	.526	.193
	Wilks' Lambda	.417	.974	80.000	314.066	.545	.196
	Hotelling's Trace	.996	.965	80.000	310.000	.566	.199
	Roy's Largest Root	.378	1.552[c]	20.000	82.000	.086	.275
AIfeaturesintegratesmoothlyintomyregularaccountingworkflow	Pillai's Trace	.813	1.045	80.000	328.000	.386	.203
	Wilks' Lambda	.398	1.033	80.000	314.066	.413	.206
	Hotelling's Trace	1.054	1.021	80.000	310.000	.440	.208
	Roy's Largest Root	.443	1.817[c]	20.000	82.000	.032	.307
AIfeaturescontributetoincreasedproductivityinmyaccountingactivit	Pillai's Trace	.646	1.110	60.000	243.000	.288	.215
	Wilks' Lambda	.480	1.101	60.000	236.527	.303	.217
	Hotelling's Trace	.843	1.091	60.000	233.000	.319	.219
	Roy's Largest Root	.399	1.614[c]	20.000	81.000	.069	.285
IfeelconfidentusingAIfeatureswithoutneedingexternalhelp	Pillai's Trace	.762	.965	80.000	328.000	.565	.191
	Wilks' Lambda	.421	.962	80.000	314.066	.571	.194
	Hotelling's Trace	.991	.960	80.000	310.000	.578	.198
	Roy's Largest Root	.449	1.840[c]	20.000	82.000	.029	.310
ThedesignAIenabledtoolsincloudaccountingisintuitiveandclear	Pillai's Trace	.864	1.130	80.000	328.000	.231	.216
	Wilks' Lambda	.372	1.120	80.000	314.066	.249	.219
	Hotelling's Trace	1.144	1.108	80.000	310.000	.269	.222
	Roy's Largest Root	.421	1.724[c]	20.000	82.000	.046	.296
LearningtouseAIdrivenfeaturesinmyaccountingplatformsiseasyforme	Pillai's Trace	.760	.961	80.000	328.000	.574	.190
	Wilks' Lambda	.426	.949	80.000	314.066	.602	.192
	Hotelling's Trace	.967	.937	80.000	310.000	.629	.195
	Roy's Largest Root	.396	1.622[c]	20.000	82.000	.067	.283
UsingAItoolsenhancestheoverallqualityoffinancialreporting	Pillai's Trace	.903	1.196	80.000	328.000	.143	.226
	Wilks' Lambda	.355	1.180	80.000	314.066	.163	.228
	Hotelling's Trace	1.199	1.162	80.000	310.000	.186	.231
	Roy's Largest Root	.406	1.666[c]	20.000	82.000	.057	.289
AIrecommendationsimprovetheaccuracyofmyaccountingwork	Pillai's Trace	.728	.912	80.000	328.000	.685	.182
	Wilks' Lambda	.440	.907	80.000	314.066	.695	.185
	Hotelling's Trace	.930	.901	80.000	310.000	.707	.189
	Roy's Largest Root	.346	1.419[c]	20.000	82.000	.137	.257
AIfunctionsreducetheeffortrequiredtohandlecomplexaccountingtasks	Pillai's Trace	.726	.909	80.000	328.000	.692	.181
	Wilks' Lambda	.439	.911	80.000	314.066	.687	.186
	Hotelling's Trace	.943	.913	80.000	310.000	.681	.191
	Roy's Largest Root	.452	1.851[c]	20.000	82.000	.028	.311
IuseAIfeaturesregularlyforactivitieslikedataentryreconciliationo	Pillai's Trace	.243	1.267[b]	20.000	79.000	.226	.243
	Wilks' Lambda	.757	1.267[b]	20.000	79.000	.226	.243
	Hotelling's Trace	.321	1.267[b]	20.000	79.000	.226	.243
	Roy's Largest Root	.321	1.267[b]	20.000	79.000	.226	.243
	Pillai's Trace	.226	1.151[b]	20.000	79.000	.319	.226

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AIassistancereducesthenumberofstepsIneedtocompleteanaccountingta	Wilks' Lambda	.774	1.151b	20.000	79.000	.319	.226
	Hotelling's Trace	.291	1.151b	20.000	79.000	.319	.226
	Roy's Largest Root	.291	1.151b	20.000	79.000	.319	.226
IfrequentlyuseAIenabledfeatureswhenperformingaccountingtask	Pillai's Trace	.169	.806b	20.000	79.000	.699	.169
	Wilks' Lambda	.831	.806b	20.000	79.000	.699	.169
	Hotelling's Trace	.204	.806b	20.000	79.000	.699	.169
	Roy's Largest Root	.204	.806b	20.000	79.000	.699	.169
ItrustAIfeaturestoprovidereliablerecommendations	Pillai's Trace	.352	2.141b	20.000	79.000	.009	.352
	Wilks' Lambda	.648	2.141b	20.000	79.000	.009	.352
	Hotelling's Trace	.542	2.141b	20.000	79.000	.009	.352
	Roy's Largest Root	.542	2.141b	20.000	79.000	.009	.352
IrelyonAIdrivenfunctionsmorethanmanualmethods	Pillai's Trace	.192	.939b	20.000	79.000	.541	.192
	Wilks' Lambda	.808	.939b	20.000	79.000	.541	.192
	Hotelling's Trace	.238	.939b	20.000	79.000	.541	.192
	Roy's Largest Root	.238	.939b	20.000	79.000	.541	.192
IbelieveAItoolsdeliveraccurateresultsmostofthetime	Pillai's Trace	.082	.352b	20.000	79.000	.995	.082
	Wilks' Lambda	.918	.352b	20.000	79.000	.995	.082
	Hotelling's Trace	.089	.352b	20.000	79.000	.995	.082
	Roy's Largest Root	.089	.352b	20.000	79.000	.995	.082
MyoverallusageifAIinaccountinghasincreasedovertime	Pillai's Trace	.172	.820b	20.000	79.000	.683	.172
	Wilks' Lambda	.828	.820b	20.000	79.000	.683	.172
	Hotelling's Trace	.208	.820b	20.000	79.000	.683	.172
	Roy's Largest Root	.208	.820b	20.000	79.000	.683	.172
ItrustAIfeaturestosupportimportantfinancialdecisions	Pillai's Trace	.201	.996b	20.000	79.000	.476	.201
	Wilks' Lambda	.799	.996b	20.000	79.000	.476	.201
	Hotelling's Trace	.252	.996b	20.000	79.000	.476	.201
	Roy's Largest Root	.252	.996b	20.000	79.000	.476	.201
IfeelcomfortablerelyingonAIdrivenoutputsinaccountingtasks	Pillai's Trace	.195	.959b	20.000	79.000	.518	.195
	Wilks' Lambda	.805	.959b	20.000	79.000	.518	.195
	Hotelling's Trace	.243	.959b	20.000	79.000	.518	.195
	Roy's Largest Root	.243	.959b	20.000	79.000	.518	.195
IbelieveAIenabledaccountingtoolsaredependable	Pillai's Trace	.231	1.186b	20.000	79.000	.289	.231
	Wilks' Lambda	.769	1.186b	20.000	79.000	.289	.231
	Hotelling's Trace	.300	1.186b	20.000	79.000	.289	.231
	Roy's Largest Root	.300	1.186b	20.000	79.000	.289	.231