Investigating Accountants' Resistance to the Adoption of Data Analytics Technology

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ABSTRACT

Some time ago, a call to action in the accounting profession was sounded: become a profession founded on data analytics or become a profession bound for the history books. Accounting firms and corporations are investing to the development of data analytics capabilities, but it is not clear whether accounting professionals are leading or are following the charge. Practitioner press indicates accountants resist the move away from Excel even as organizations hire data scientists rather than accountants. This paper uses Status Quo Bias Theory to examine the resistance to emerging data analytics technology by accounting and finance professionals. Deviating from the predictions of the theory, the results indicate the perceived value of a new technology does not mediate the effect of switching benefits and costs on resistance. Rather, switching benefits and perceived value are aligned as a single factor to reduce resistance, while switching costs directly increase resistance. This calls for a deeper investigation into the way these professionals apply cost-benefit analyses and other intangible factors when resisting or accepting a change in technology. Researchers have focused substantial effort toward data analytics in education and business, this study suggests that a troubling number have not, and may not adopt.

1.0 Introduction

Data analytics has quickly become one of the most important disruptive issues facing the accounting profession. Almost daily, the practitioner press touts this transformation as the most critical skillset for accountants, and the path for the profession to avoid obsolescence. If we do not embrace and adapt to the new world of big data, data science, and by extension, artificial intelligence and automation, the accounting profession faces the likely reality of becoming the "weavers of the 21st century". A cursory Google search of 'data analytics and accounting' will return page after page of articles that alternate between warnings of dire consequences and proclamations of fantastic opportunities that lie ahead for the profession. A literature search provides ample evidence that academic researchers agree, having studied a variety of areas affected by data analytics (e.g., Appelbaum, Kogan, and Vasarhelyi 2017; Richins, Stapleton, Stratopoulos, and Wong 2017; Schneider, Dai, Janvrin, Ajayi, and Raschke 2015; Dzuranin, Jones, and Olvera 2018). The call to action is obvious: the data-driven revolution is here, and the accounting profession occupies a primary role in it.

While the urgency for accountants to utilize data analytics is clear, there is little evidence of whether accounting professionals are actually heeding this call. Making the jump to a data-driven mindset and embracing emerging analytics technology requires a virtual overhaul of the entire profession. The recent, near-visceral reaction of the profession at large to a *Wall Street Journal* article ((WSJ) Shumsky 2017a, b) calling for the retirement of Excel indicates some accountants are apparently still fighting to maintain the familiar. The reaction to this article indicates many accountants ignore, refute, or otherwise challenge the possibility that emerging data analytics technology is a more appropriate, better option than Excel. The warnings have been sounding for years, the vendors have been peddling their tools, and the researchers have

been offering solutions, yet some accountants are still "clinging to the warm blanket" provided by Excel. Why? As a former chair of the AICPA noted in an opinion piece titled "Why Accountants Should Embrace, Not Avoid, Emerging Technologies", finance and accounting professionals have been content to "wait and see and to leave the new technology to others. The mantra could well be: 'If it ain't broke, why fix it?'" (Ellison-Taylor 2019, np). We stubbornly cling to this at our own peril. On the other hand, accounting firms and organizations are not content to wait, and are investing heavily in emerging technology. They are ignoring accountants' reluctance and instead replacing them with data scientists and technology experts willing to embrace the required skillset. The roles accountants should be playing in these organizations are being redefined for people who are not sitting on the sidelines of technology (Tysiac and Drew 2018).

We recognize that a number of accounting researchers, educators, and practitioners have embraced data analytics and other emerging technology. This is particularly evident in research guiding current curriculum changes to prepare new accountants to enter the profession. These first-movers have made significant contributions toward the development of innovative, agile, and tech-savvy graduates ready to hit the ground running (e.g., Dzuranin et al. 2018; Ballou, Heitger, and Stoel 2018). We are concerned about the significant number of accountants already in practice, and were unable to find research evidencing their acceptance of emerging data analytics technology. If accountants' reactions to a *WSJ* suggestion for Excel's retirement, and if organizations' preferences toward data specialists over accountants are any indication, it may be that a troubling number of practicing accountants have not accepted the future of the profession is now. The logical question that follows is *why* are they are resisting adoption. Understanding the answer to this question is critical for the development of interventions to resistance and

incentives for acceptance. In this paper, we aim to address this gap in the literature by drawing from research on IT resistance. Specifically, we utilize Kim and Kankanhalli's (hereafter, K&K 2009) Status Quo Bias Theory (SQBT).

K&K (2009) developed SQBT as an integration of the status quo bias concept with several models and theories of IT use, including the Technology Acceptance Model (TAM, Davis 1989), the Theory of Planned Behavior (TPB, Ajzen 1991), and the Equity-Implementation Model (EIM, Joshi 1991). This integration allows for the investigation of a more comprehensive set of influences on users' decisions to resist or accept an emerging technology. These influencers include switching costs, switching benefits and perceived value, as well as self-efficacy, organization support, and colleague opinion. Our primary research objective in this exploratory investigation is: Does Status Quo Bias Theory explain professional accountants' resistance to switch from Excel to emerging data analytics tools?

We develop a survey instrument from the K&K (2009) integrated model of SQBT to test our hypotheses. A usable sample of 192 practicing accountants and business professionals completed the survey. Our findings deviate from K&K (2009) in a number of ways. We find that switching benefits and switching costs are directly related to the resistance to change, not indirectly through a mediator variable of perceived value. It appears the accounting and finance professionals in our sample perceive the value and the benefits of the switch as the same construct, and that perceived value is not significantly affected by the switching costs. None of the hypothesized antecedents to switching costs are significant, but colleague opinion does affect switching benefits and resistance to change.

We contribute to the literature by exploring why some accounting and finance professionals continue to resist new and emerging data analytics technology. Researchers can

develop and study interventions to address professionals' status quo biases, and organizations can then implement the interventions to encourage acceptance. Accounting educators can create curriculum to teach technology tools and to foster a spirit of adaptability in students, breaking down resistance before they enter the profession. Professionals can use these results to understand their own current attitudes toward emerging data technology and address biases toward the status quo. Researchers have focused substantial effort toward data analytics in education and business, but have not documented whether accounting professionals have actually adapted to the new reality. We suggest that a troubling number have not, and contribute to the literature by exploring why some continue to resist.

The revolutionary impact of data analytics on the accounting profession is no longer up for debate. The vice chair of the AICPA, Bill Reeb, went even further than suggesting accountants were content to "wait and see", instead lamenting that accountants are "going to go kicking and screaming" into the future (Tysiac and Drew, 4). Shouldn't we be running head first to the front of the pack instead? Why are accountants resisting? Why are we still kicking and screaming?

2.0 Literature Review and Hypotheses

Data Analytics and Excel

It is difficult, if not impossible, to avoid hearing about the surging tide of data analytics. For some time stakeholders in the accounting discipline have sounded the warning that the profession must embrace and adapt to a data analytics mindset or face extinction. Accounting scholars have researched the integration of data analytics in the curriculum (e.g., Dzuranin et al. 2018; Ballou et al. 2018); the effects of data analytics in auditing and managerial accounting (e.g., Brown-Liburd and Vasarhelyi 2017; Vasarhelyi, Kogan, and Tuttle 2015; Applebaum et al.

2017); and predictions on the fate of the accounting profession as a whole (e.g., Tysiac and Drew 2018; Richins et al. 2017). Although all manner of technology has been pressuring the accounting profession for decades, the speed and magnitude of the changes brought about by data analytics is arguably one of the most transformational in modern accounting history. As a result, large accounting firms and corporations have committed significant resources to developing their technological competencies. This includes heavy investment in the emerging tools as well as in staff that are highly skilled in data analytics (e.g., Cohn 2017). The concern is that accountants may not be the most sought after professionals to fill these roles. Some evidence seems to indicate this investment is going towards non-accounting professionals. As one consultant noted: "It's not just about bringing in the brightest CPAs and CFAs anymore. Fill your team with data scientists and broaden the notion of what a modern financial team truly is" (Silverman 2019, np).

In order to take advantage of this space, accountants must be ready and willing to master the technology that supports unstructured data. While researchers have focused substantial effort toward data analytics in education and business, it is not clear whether accounting professionals have actually adapted to the new reality. If we accept the assertions of some practitioner press, it appears a troubling number have not. Why, in the face of near constant warnings of impending obsolescence, are some accountants resisting the technology? We suggest the professionals' individual-level biases toward maintenance of the status quo contribute to the tendency to resist, and draw on the substantial body of research on resistance in the information systems literature.

IT Resistance and Status Quo Bias

A number of theoretical perspectives have been proposed to explain resistance, such as the Technology Acceptance Model ((TAM) Davis 1989), the Theory of Planned Behavior

((TPB), Ajzen 1991), and the Equity-Implementation Model ((EIM), Joshi 1991). In 2009, K&K proposed SQBT as an alternative approach to understanding the phenomena of IS user resistance. The integrated theory adds concepts from TPB and EIM to the status quo bias perspective, with the objective of offering a new and enhanced method of understanding behavior surrounding new IS implementations. The status quo bias perspective was first introduced by Samuelson and Zeckhauser (1988) as a lens to study economic decision-making behavior. In a series of experiments and observations, they found support for a status quo bias in the observed and actual choices of adults regarding their health care and retirement plans. K&K (2009) indicate EIM is relevant because it proposes a cost-benefit analysis that aligns with the concepts of the status quo bias perspective. They utilize TPB instead of other theoretical approaches because of its comprehensiveness in explaining technology acceptance. In sum, the integrated SQBT aims to explain an individual's preference for maintaining their current state through cost-benefit analysis, perceived value, colleague opinion, and self-efficacy and organizational support for change.

Hypotheses

Rational decision-making principles indicate the perceived value of any choice is a function of the net benefits of that choice (Kahneman and Trversky 1979). In regards to SQBT, this requires consideration of the perceived switching benefits (the perceived utility a user would enjoy in switching from the status quo to the new IS" (K&K, 573)) and perceived switching costs ("the perceived disutility a user would incur in switching to the new IS" (K&K, 572)). Each of these is expected to affect the perceived value of the new IS. Because individuals generally act in their own self-interest, they choose to maximize value by assessing net benefits and then resisting or accepting the new tool (Sirdeshmukh et al. 2002). In relation to our study, we suggest

that practicing accountants will assess the value of new data analytics technology through this rational, cost-benefit approach.

> H1: The perceived value of the new data analytics tool is negatively associated with an individual's resistance to change from Excel to a new data analytics tool.

According to K&K, switching costs include three components from SQBT: transition costs, uncertainty costs, and sunk costs. Transition costs are based on Kahneman and Tversky (1979)'s research that identified individuals' resistance to change due to their motivation to avoid losses. Uncertainty costs arise in regards to individuals' aversion to feelings of incompetence (Brown and Venkatesh 2005). Finally, sunk costs increase resistance to change because of past investments in the current technology. SQBT proposes the aggregate of these costs are directly associated with an individual's resistance to switch:

> H2: Switching costs are positively associated with an individual's resistance to change from Excel to a new data analytics tool.

In addition to the direct effect of switching costs on user resistance, these costs are expected to influence user resistance indirectly through their influence on perceived value. As noted previously, this value is a function of a rational individual's assessment of the switching costs and switching benefits (Kahneman and Trversky 1979). Switching benefits may result from improvements in job performance such as efficiency, effectiveness, and quality. We propose the following two hypotheses:

> H3: Switching costs are negatively associated with an individual's perceived value of a new data analytics tool.
> H4: Switching benefits are positively associated with an individual's perceived value of a new data analytics tool.

The TPB brings several concepts to the integrated SQBT, including subjective norms and perceived behavioral controls (Ajzen 1991). SQBT conceptualizes the perceived behavioral

controls of TPB as self-efficacy and organizational support for change. These represent internal and external forces, respectively, for control over a change. Control is an important influence because individuals who feel some sense of control over a situation are more likely to feel confidence in their ability to adjust to a change. Internally, this manifests as self-efficacy, and individuals with lower levels of self-efficacy are more likely to feel threatened by change and fearful of their own ability to master the new situation (Bandura 1995). According to the SQBT, this results in the expectation that self-efficacy will have an inverse relationship with resistance to change from Excel to a new data analytics tool. At the same time, self-efficacy may also influence an individual's assessment of switching costs. This is because higher levels of self-efficacy for change are associated with lower perceptions of uncertainty (Bandura 1995; Compeau et al. 1999), which we identified previously as a component of switching costs. We state these expectations formally:

H5: Self-efficacy for a change from Excel to a new data analytics tool is negatively associated with user resistance to change.
H6: Self-efficacy for a change from Excel to a new data analytics tool is negatively associated with perceived switching costs of the change.

External controls can also exert an influence over a user's resistance to change to a new IS. K&K (2011, 573) define organizational support for change as "the perceived facilitation provided by the organization to make users' adaptation to new IS-related change easier." This is an external control because the organization can create a culture of acceptance and positivity around the new technology. By fostering of cultural support for change, management can encourage users to develop a more positive attitude toward the new tool. This will directly reduce their resistance to change. More specifically, the organization can provide resources such as training and dedicated time to employees in order to assist them in adopting the new technology. Given these resources,

users may perceive reduced difficulty in adapting, which can result in reduced transition costs and indirectly reduce resistance to change. Stated formally:

H7: Organizational support for a change from Excel to a new data analytics tool is negatively associated with user resistance to change.
H8: Organizational support for a change from Excel to a new data analytics tool is negatively associated with perceived switching costs of the change.

SQBT conceptualizes subjective norms as colleague opinion. This social norm has been identified as a salient influence on behavior at work (Lewis et al. 2003). Individuals seek social approval and fear negative reactions from their colleagues, resulting in the tendency to conform (Ajzen 2002). Accordingly, we expect the acceptance of or resistance to a change from Excel will be directly affected by colleagues' opinion regarding the new data analytics tool. Colleague opinion has also been identified as an informational influence – that is, individuals' initial recognition of switching costs and benefits may be influenced by the information they receive from colleagues (Bunkrant and Cousineau 1975). Because colleagues exert a strong, socially salient norm, their opinions are internalized by each other on a daily basis. If colleagues present a positive opinion toward a change from Excel to a new tool, it can reduce the uncertainty of the change, thereby reducing switching costs. Similarly, colleagues' promotion of the advantages of a new technology can manifest in an increased assessment of the switching benefits. Stated formally:

H9: Colleague opinion is negatively associated with an individual's resistance to change from Excel to a new data analytics tool.
H10: Colleague opinion of a change from Excel to a new data analytics tool is negatively associated with perceived switching costs of the change.
H11: Colleague opinion of a change from Excel to a new data analytics tool is positively associated with perceived switching benefits of the change.

We present our hypothesized model of SQBT in Figure 1.

<<Insert Figure 1 here>>

3.0 Method

Instrument

We use K&K's (2009) instrument to test our hypotheses. The instrument includes several scales adopted from prior research and others developed by those authors, detailed as follows:

- **PVL** = Three questions for **Perceived Value**, adapted from Sirdeshmukh et al. (2002)
- **SW**B = Four questions for **Switching Benefits**, developed by K&K (2009) from similar constructs of Moore and Benbasat (1991)
- **SWC** = Four questions for **Switching Costs**, adapted from Jones et al. (2000)
- **CGP** = Three questions for **Colleague Opinion**, developed by K&K (2009) from research by Venkatesh and Davis (2000)
- **SFC** = Three questions for **Self-Efficacy**, adapted from Taylor and Todd (1995)
- **OGS** = Three questions for **Organizational Support**, developed by K&K (2009) from research by Thompson et al. (1991)
- **RTC** = Four questions on user **Resistance to Change**, developed by K&K (2009) from the framework of resistance behaviors created by Bovey and Hede (2001)

Our survey instrument concludes with standard demographic questions. Please see the instrument in the Appendix.

Data collection and participants

We surveyed professional accountants from different areas of sub-discipline experience and through several channels. Access to participants in the IMA 2018 Annual Conference & Expo Research Lab was granted through the IMA Research Foundation. while access to participants in chapter meetings of state societies of Certified Public Accountants (CPAs), the Institute of Management Accountants (IMA), the Institute of Internal Auditors (IIA) and accounting advisory boards was granted through the authors' professional relationships. A usable sample of 192 working accounting and finance professionals was obtained. Females (males)

comprise 41.8% (58.2%) of the sample, and the average age (business experience) of respondents is 41.5 (18.4) years. See full descriptive information on participants in Table 1.

<<Insert Table 1 here>>

Instrument validation

The survey instrument was evaluated by K&K (2009) for both convergent validity and discriminant validity of the measurement model, and both were established in their research. We used SPSS to perform similar tests on our results, by conducting Principle Components Analysis (PCA) with Varimax rotation. This was performed to independently determine (and confirm expected) factor loadings of items using data collected for this study in the accounting/finance context. Factor analysis findings are shown in Table 2.

<<Insert Table 2 here>>

The issue revealed by our factor analysis is that two factors of Switching Benefits and Perceived Value are strongly loading together. In the K&K model, Perceived Value appears as a mediator between the antecedents of Switching Benefits and Switching Costs and the dependent variable of Resistance to Change. Here, there is no discrimination between Switching Benefits and Perceived Value and hence no differentiation between the variables. Two survey items fail to load adequately on their latent factors, the fourth item for Switching Costs (SWC4) and first item for Self-Efficacy (SFC1), with loadings of 0.483 and 0.566 respectively. For purposes of model testing in the rest of this section, these two items are eliminated. These two items are not included in the summative measures calculated from the items with sufficient loading on their latent factor. The remaining items display loadings above 0.70, and are deemed acceptable and all four items are retained for the Resistance to Change latent factor.

George and Mallery (2003) indicate the following scale to interpret the results of Cronbach's alpha: values > .9 (Excellent), > .8 (Good), > .7 (Acceptable), > .6 (Questionable). These results show that four of the seven latent factors display a Cronbach's alpha greater than 0.90 which is excellent, and the other three are above .80 with the lowest being 0.83. Composite reliability (CR) is also acceptable with two values being above .90 and all well above .80, with lowest value of 0.86. See Table 3.

<< Insert Table 3 here>>

Given that items for both Switching Benefits and Perceived Value loaded onto the same rotated factor, we will perform two versions of the remaining analysis. First, we proceed with the model and hypotheses testing as originally proposed. We do this because one objective of this research is to examine integrated SQBT, as proposed by K&K (2009), in the context of accounting and finance. Second, we drop Perceived Value as a construct in the model and analyze the revised model without this mediator. This process may provide some insight into potential differences in the accounting/finance context and suggest future research to further refine the theory and model.

4.0 Results

Hypotheses Testing

The hypotheses for the originally proposed model were tested using Least Squares Linear regression. These results are summarized in Figure 2, retaining all factors based on the K&K SQBT model for influences on the outcome factor of Resistance to Change, as explained above.

<<Insert Figure 2 here>>

The results indicate that Perceived Value (H1), Switching Costs directly (H2) and colleague support (H9), had significant effects on user Resistance to Change, explaining 38.9% of its

variance. The effect of Organizational Support on Resistance to Change is marginally significant (H7). Switching Costs did not significantly affect Perceived Value (H3), and no variables significantly affected Switching Costs (Self-Efficacy (H6), Organizational Support (H8), and Colleague Opinion (H10)). Finally, Colleague Opinion significantly effects Switching Benefits (H11), and Switching Benefits is significantly affecting Perceived Value (H2). However, any conclusions from this result are questionable at best, considering the PCA loadings discussed previously. We include this here for completeness of SQBT testing, and for comparison to our proposed revised model discussed next.

To remedy the lack of differentiation between items for Switching Benefits and Perceived Value, an alternative model is proposed and tested wherein the mediation variable of Perceived Value is dropped. This exploratory model aims to explore the SQBT model employed in the accounting/finance context, since the Perceived Value factor does not successfully perform the mediation role expected in the SQBT model (K&K 2009). As presented in Figure 3, Switching Benefits (H1-Alt) and Switching Costs (H2) have a direct, significant effect on Resistance to Change, explaining 40.9% of its variance. Self-Efficacy (H5), Organizational Support (H7), and Colleague Opinion (H9) all indicate marginally significant effects on Resistance to Change. When these three variables are included in the model, the explanatory power increases to 46.0%, providing support for their relevance to the model. Relationships between these three variables and Switching Benefits and Switching Costs are largely retained from the original model.

<<Insert Figure 3 here>>

Table 4 provides a summary of hypothesis testing for both models, plus the findings of the original K&K (2009) study for comparison (Support, No Support, or Marginal Support).

<<Insert Table 4 here>>

5.0 Discussion of Results

In this paper, we explore factors influencing resistance to use new tools for data analysis in accounting instead of the familiar tools (particularly, Excel). As vast amounts of business data are now available to companies, it is critical to understand the reaction of these experienced, working professionals to new and emerging data analytics technology. Our survey used existing items and a model based on SQBT (K&K 2009), with a sample of 192 working accounting and finance professionals. Results indicate that the equity theory represented in the K&K (2009) model of Switching Costs, Benefits, and Resistance to Change does not operate fully as expected in this context. In the findings, the construct of Perceived Value is very closely aligned with Switching Benefits alone, and does not seem to incorporate effects of Switching Costs. Further, none of the hypothesized antecedents to Switching Costs (Colleague Opinion, Self-Efficacy and Organizational Support) are found to be influential. Thus, findings show Switching Costs lack influential antecedents and have no subsequent influence on Perceived Value. This calls for a deeper investigation into the way these professionals adapt and apply their quantitative cost-benefit equity models into this context.

Also, the finding that Switching Benefits load on the same factor as Perceived Value would indicate Switching Costs may not be considered as part of the Perceived Value mediator, yet Switching Costs do appear to have direct influence on Resistance to Change. Thus, unlike in the K&K model, as used in the context of general adoption of IS, in this accounting/finance context Switching Benefits and Switching Costs are not both mediated by Perceived Value when influencing Resistance to Change. The findings regarding direct influences on Resistance to Change are more similar to K&K's findings, but with different weightings and with the addition of Colleague Opinion as a significant influence.

Due to the factor loading issues, and the greatly diminished mediating role of Perceived Value, an alternative SQBT model was proposed to reveal how each component of the model (Switching Costs and Switching Benefits) directly impact the Resistance to Change construct. Given the extensive use of quantitative cost-benefit analysis used in accounting/finance, it is quite surprising that findings indicate Perceived Value is based solely on Switching Benefits. In K&K (2009), Resistance is influenced directly by Switching Costs, and influenced indirectly by both Switching Costs and Switching Benefits through the mediator of Perceived Value.

It is important to note this discrepancy in the results, because it indicates accounting and financial professionals in our sample are able to disassociate costs from value. At the same time, Switching Costs do significantly increase the Resistance to Change. Understanding this relationship suggests organizations should focus their efforts more on reducing the costs for employees, not on demonstrating the benefits or the value of the new technology. It is likely accounting and finance professionals have been sufficiently educated on the benefits that advanced data technology offers, and no longer need to be convinced.

The remaining variables in the alternative model yield mixed results. Organizational Support and Self-Efficacy are only marginally significant at best, but Colleague Opinion indicates some potential influence. It significantly increases Switching Benefits, and shows promise towards reducing Resistance. Prior research on these variables and their roles in resistance is similarly mixed (e.g., Sykes 2015; Tong, Tan, and Teo 2015; Lewis et al. 2003; Venkatesh 2000), and therefore, it is apparent more research attention is needed.

One possible explanation for this, demanding additional exploratory testing, may lie in potential sub-dimensions of the variables. For example, the individual items making up the Resistance to Change construct may indicate a possible dichotomy between an accountant's

personal resistance to change versus the professional's abstract agreeableness to adopting change to comply with organizational policy. Reactions to personally adopting/resisting a change may differ markedly from the individual's support for a company policy which asks the organization (and other individuals) to adopt the new technology to benefit broader company advancement. At the same time, colleague opinion may differ in its effect on resistance if a colleague is truly a peer or a supervisor. These examples are just a few to emphasize the importance of refining and understanding the possible dimensions of the constructs. This represents a worthwhile area for future research.

Further, the antecedents of Switching Costs are all non-significant, in both the original SQBT model and in our alternate model, indicating potentially different and unknown influences are used by accounting and finance professionals when considering intangible analysis of switching costs. Accordingly, future research is needed to expand or contract the model to refine our understanding of the resistance to change. Lastly, alternate model results were conducted because of the findings in the confirmatory factor analysis. However, the results of this factor loading issue (with Perceived Value and Switching Benefits loading together) remains an issue and findings should be interpreted with caution.

Conclusion

The conclusions of our study are limited by those common to all surveys, including self-selection bias, time constraints, and lack of incentives. However, we can surmise that practicing accounting professionals have a vested interest in the data analytics revolution, and therefore paid closer attention to their responses. The fact that we were able to gather responses from practicing professionals is a strength of our study. We also recognize that our survey required a forced, scaled response to structured questions, which limits respondents' ability to explain

nuances in their perceptions. Research utilizing field studies or interviews of practicing accountants will help triangulate our findings.

Such research will also allow for the exploration of a related question that cannot be answered with our survey: whether accountants foresee the use of Excel for simple, specific tasks as a driving factor in resistance. In other words, is their apparent aversion to giving up Excel because this is too much of a warm blanket, a radical choice? Perhaps accountants in our survey (and those reacting en masse to the *WSJ* article) are adapting to emerging data analytics tools for primary tasks, but continuing to use Excel for easier, repetitive jobs they can complete by jumping in and out of Excel quickly. Why bother transferring everything to a data analytics tool if it can easily be done in Excel? Can't we have both? We suggest two possible problems with this attitude. First, using a second (or third) software creates unnecessary storage needs, updating needs, security issues, costs, and risks. We continue to risk errors, lack of currency, and lack of functionality by downloading data to Excel rather than embracing a sophisticated data analytics mindset. Second, by clinging to Excel, we have gained a reputation for "kicking and screaming", something that may be driving accounting firms and organizations to redefine their jobs for data scientists rather than accountants. This is not sustainable and the survival of the accounting profession depends upon its ability to be leaders into the new frontier.

Multiple avenues for continued research exists. Although not explicitly included in their status quo bias perspective, Samuelson and Zeckhauser (1988) conclude from their research that a status quo choice acts as a "psychological anchor". That is, the strength of the individual's prior commitment to the status quo choice will establish the strength of the individual's anchor on the status quo. This may relate to the length of time an individual has used their prior technology, the intensity of their use, and their effort spent in learning it. Accordingly, future

research is needed to determine whether these individual characteristics, which we collectively call ‘commitment’, are positively related to the resistance to change to a new data analytics tool. Because this connection was not included and validated in the integrated SQBT, we do not include this in the formalized model, but rather pose this as a future research question.

Similarly, it would be interesting to explore accounting and finance professionals’ previous experience with technology change. Greenwood, Ganju, and Angst (2019) found disruptive technologies were more likely to cause resistance and employee exodus as the number of previously disruptive events increased. In other words, rather than encouraging the development of an agile mindset, numerous changes in technology exacerbated negative reactions. This raises the question of whether accounting/finance professionals who are resistant to change remain so because they ‘have seen this kind of hype before’ in situations such as ERP, e-commerce, and similar ‘revolutionary’ disruptions.

One of the most important lies in the development of interventions for resistance. How can organizations create a culture of agility and innovation throughout their employees? This is not exclusive to data analytics. Even if accounting professionals adapt to data analytics, the next wave of technology change is already upon us. From automation to artificial intelligence to the Internet of Things to Blockchain and digital currency, we no longer have the luxury of time. We hope that the findings of our study will encourage more research into this seemingly entrenched (whether real or perceived) philosophy. The introduction of new technology is the only constant; it has become, in fact, the status quo.

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Table 1
Descriptive Statistics

	Number	Percent
Gender (n=189)		
Female	79	41.8%
Male	110	58.2%
Average Age (n=178)	41.5 years	
Highest Degree Completed (n=188)		
Some undergraduate college credit	1	1.9%
Bachelors	66	35.8%
Some graduate school credit	40	20.2%
Graduate degree	81	32.1%
Average Business Experience (n=178)	18.4 years	
Position		
Entry level	38	20.8%
Supervisory level	32	17.5%
Middle Management level	59	32.2%
Executive Management level	45	24.6%
Board of Directors	9	4.9%
Size of Business (employees) (n=190)		
0-100	49	25.8%
101-500	57	30.0%
501-1000	29	15.3%
1001-5000	26	13.7%
5001-10000	13	6.8%
>10000	16	8.4%
Type of Accounting Information System		
General Ledger (e.g., Quickbooks and Sage50)	46	24.6%
Business Management System (e.g. Microsoft Dynamics GP)	27	14.4%
ERP (e.g., Netbooks, Netsuite, or SAP)	62	33.2%
In-house, proprietary system or other legacy system	16	8.6%
Unsure	23	12.3%
Other (e.g., customized industry system such as commodities)	13	6.9%

Table 2
Factor Loadings of Principal Component Analysis with Varimax Rotation

Items	1	2	3	4	5	6
PVL1	0.815	-0.213	-0.009	0.183	0.051	0.129
PVL2	0.851	-0.160	0.074	0.131	-0.005	0.182
PVL3	0.918	-0.142	0.004	0.050	-0.037	0.068
SWB1	0.860	-0.267	0.050	0.217	-0.012	0.023
SWB2	0.886	-0.211	0.000	0.231	-0.071	0.022
SWB3	0.872	-0.250	0.041	0.216	-0.063	0.099
SWB4	0.839	-0.314	0.141	-0.016	-0.046	0.104
SWC1	0.024	0.049	-0.127	-0.066	0.824	0.190
SWC2	0.011	0.089	0.037	0.011	0.844	-0.228
SWC3	-0.065	0.184	0.094	0.035	0.877	-0.083
SWC4	-0.265	0.488	-0.011	-0.281	**0.483**	-0.043
RTC1	-0.305	0.817	-0.108	-0.156	0.080	-0.043
RTC2	-0.270	0.854	-0.064	-0.140	0.110	-0.095
RTC3	-0.378	0.714	-0.135	-0.033	0.167	-0.190
RTC4	-0.423	0.706	-0.150	-0.114	0.149	-0.121
CGP1	0.225	-0.046	0.101	0.882	-0.046	0.063
CGP2	0.287	-0.169	0.087	0.872	-0.053	0.120
CGP3	0.128	-0.207	0.326	0.710	0.018	0.088
SFC1	0.294	-0.280	0.289	0.309	-0.001	**0.566**
SFC2	0.181	-0.034	0.132	0.024	-0.119	0.919
SFC3	0.071	-0.166	0.288	0.119	-0.001	0.830
OGS1	0.074	-0.090	0.913	0.136	-0.003	0.158
OGS2	0.038	-0.108	0.939	0.095	-0.007	0.203
OGS3	0.029	-0.099	0.910	0.178	0.007	0.139

PVL = Perceived Value
SWB = Switching Benefits
SWC = Switching Costs
RTC = Resistance to Change
CGP = Colleague Opinion
SFC = Self-Efficacy
OGS = Organizational Support

Table 3
Reliabilities, Convergent and Discriminant Validities, and Correlations Between Latent Variables

	Mean (SD)	ICR	CR	PVL	SWB	SWC	RTC	CGP	SFC	OGS
PVL	**4.28 (1.48)**	**0.94**	**0.90**	**0.86**						
SWB	**4.30 (1.52)**	**0.96**	**0.92**	0.84**	**0.87**					
SWC	**5.01 (1.36)**	**0.83**	**0.89**	0.00	-0.05	**0.85**				
RTC	**2.82 (1.38)**	**0.90**	**0.86**	-0.49**	-0.59**	0.28**	**0.78**			
CGP	**3.69 (1.20)**	**0.86**	**0.86**	0.37**	.427**	-0.08	-.41**	**0.83**		
SFC	**3.76 (1.29)**	**0.87**	**0.87**	0.24**	.213**	-0.13	-.33**	.28**	**0.88**	
OGS	**3.38 (1.45)**	**0.95**	**0.94**	0.13	.148*	-0.03	-.29**	.38**	.42**	**0.92**

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).
ICR = Cronbach's Alpha of Internal Consistency Reliability
CR = Composite Reliability
Diagonal elements are the Square Root of Average Variance Extracted (AVE)
Off diagonal elements are correlations among latent constructs

PVL = Perceived Value
SWB = Switching Benefits
SWC = Switching Costs
RTC = Resistance to Change
CGP = Colleague Opinion
SFC = Self-Efficacy
OGS = Organizational Support

Table 4
Summary of Hypothesis Testing

Hypotheses	**SQB Model Hypotheses**	**Alternate SQB Model, no Mediation**	**SQB Model K&K 2010**
H1: PVL → RTC	**Supported** (-)	NA (dropped PVL)	**Supported (-)**
[H1-Alt: SWB→ RTC]	NA	**Alt: Supported (-)**	NA
H2: SWC →RTC	**Supported** (+)	**Supported (+)**	**Supported (+)**
H3: SWC → PVL	Not Supported	NA (dropped PVL)	**Supported (-)**
H4: SWB → PVL	Multi-colinear **(+)** (load on 1 PCA factor)	NA (dropped PVL)	**Supported (+)**
H5: SFC → RTC	Not Supported (-)	**Marginal Support (-)**	Not Supported
H6: SFC → SWC	Not Supported (-)	Not Supported	**Supported (-)**
H7: OGS → RTC	**Marginal Support** (-)	**Marginal Support** (-)	**Supported (-)**
H8: OGS → SWC	Not Supported (+)	Not Supported	Not Supported
H9: CGP → RTC	**Supported** (-)	**Marginal Support** (-)	Not Supported
H10: CGP → SWC	Not Supported (-)	Not Supported	**Supported (-)**
H11: CGP → SWB	**Support (+)**	**Supported (+)**	**Supported (+)**

FIGURE 1

Hypothesized Model

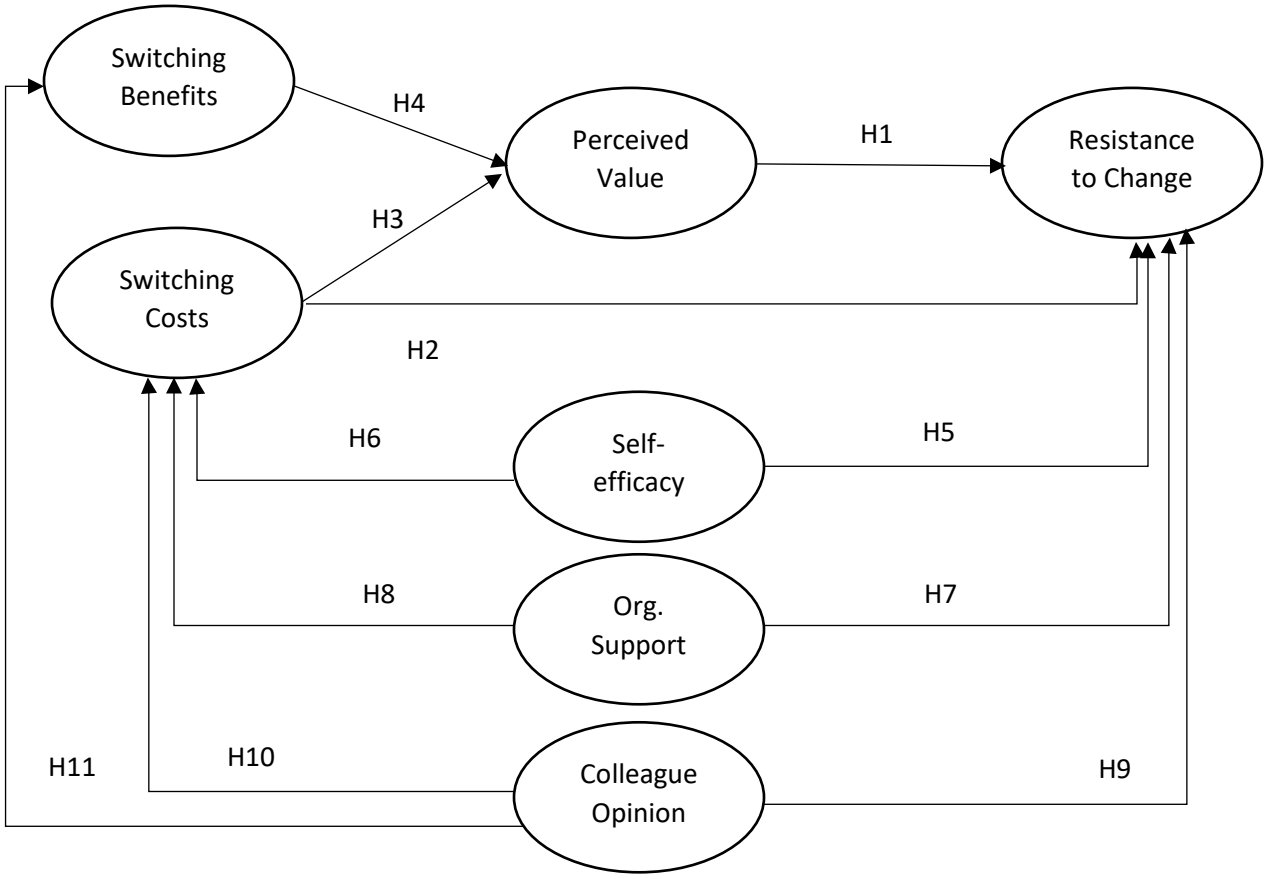


FIGURE 2
Results of Testing of Original Model

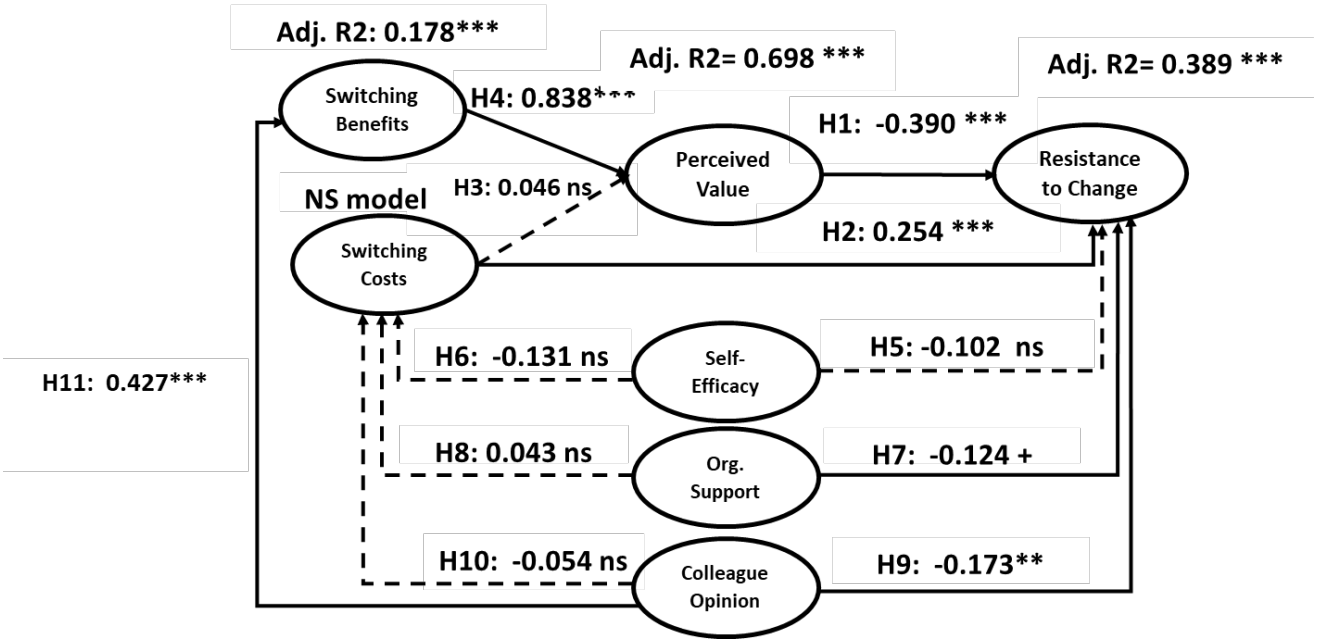
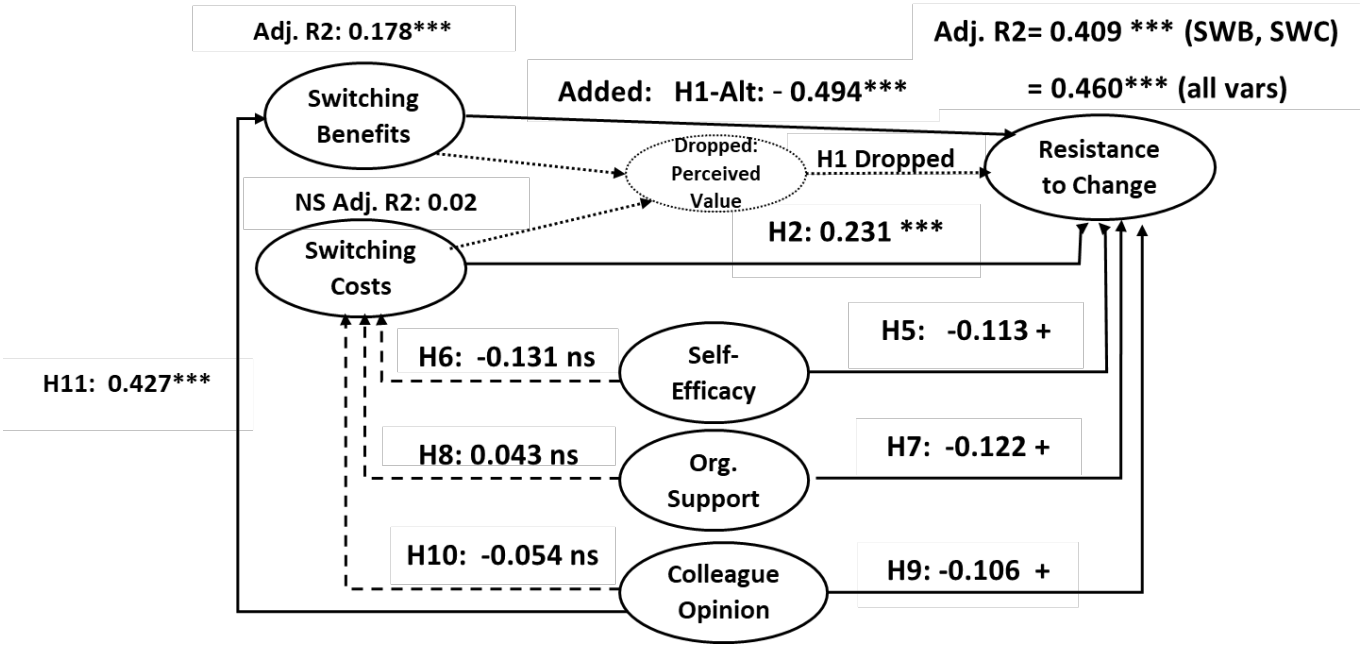


FIGURE 3
Results of Testing of Alternate Model
(Removed Perceived Value Mediator)



Appendix
Instrument

	Scale: 1=Very UNLIKELY to use to **7=Very LIKELY to use**	
1	Considering the time and effort that I have to spend, the change to the new way of working with the non-Excel, Data Analysis tool is worthwhile.	PVL1
2	Considering the loss that I incur, the change to the new way of working with the non-Excel, Data Analysis tool is of good value.	PVL2
3	Considering the hassle that I have to experience, the change to the new way of working with the non-Excel, Data Analysis tool is beneficial to me.	PVL3
4	Changing to the new way of working with the non-Excel, Data Analysis tool would enhance my effectiveness on the job than working in the current way.	SWB1
5	Changing to the new way of working with the non-Excel, Data Analysis tool would enable me to accomplish relevant tasks more quickly than working in the current way).	SWB2
6	Changing to the new way of working with the non-Excel, Data Analysis tool would increase my productivity than working in the current way.	SWB3
7	Changing to the new way of working with the non-Excel, Data Analysis tool would improve the quality of the work I do than working in the current way.	SWB4
8	I have already put a lot of time and effort into mastering the current way of working.	SWC1
9	It would take a lot of time and effort to switch to the new way of working with the non-Excel, Data Analysis tool.	SWC2
10	Switching to the new way of working with the non-Excel, Data Analysis tool could result in unexpected hassles.	SWC3
11	I would lose a lot in my work if I were to switch to the new way of working with the non-Excel, Data Analysis tool.	SWC4
12	I will not comply with the change to the new way of working with the non-Excel, Data Analysis tool.	RTC1
13	I will not cooperate with the change to the new way of working with the non-Excel, Data Analysis tool.	RTC2
14	I oppose the change to the new way of working with the non-Excel, Data Analysis tool.	RTC3
15	I do not agree with the change to the new way of working with the non-Excel, Data Analysis tool.	RTC4
16	Most of my colleagues think the change to the new way of working with a Non-Excel, Data Analysis tool is a good idea.	CGP1
17	My peers are supportive of the change to the new way of working with a Non-Excel, Data Analysis tool.	CGP2
18	Most people whom I deal with in my job encourage my change to the new way of working with a Non-Excel, Data Analysis tool.	CGP3
19	Based on my own knowledge, skills, and abilities, changing to the new way of working with a Non-Excel, Data Analysis tool would be easy for me.	SFC1
20	I am able to change to the new way of working with a Non-Excel, Data Analysis tool without the help of others	SCF2
21	I am able to change to the new way of working with a Non-Excel, Data Analysis tool reasonably well on my own.	SFC3

22	The company provides me guidance on how to change to the new way of working with a Non-Excel, Data Analysis tool.	OGS1
23	The management provides the necessary help and resources to enable me to change to the new way of working with a Non-Excel, Data Analysis tool.	OGS2
24	I am given the necessary support and assistance to change to the new way of working with a Non-Excel, Data Analysis tool by the company.	OGS3