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Acceptance and use of data visualization technologies in mining short interval control systems (SIC)

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Abstract

This study examines the impact of miners' performance expectancy, effort expectancy, social influence and facilitating conditions on digital visualization short interval control systems adoption. We propose a set of four hypotheses adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT). Data from a survey of underground miners was analyzed to validate our proposed hypotheses. Our study found that Performance Expectancy does not affect Digital Visualization SIC Adoption, while Effort Expectancy positively impacts user adoption. This research contributes to the emerging literature on the adoption and use of data analytics as a capability that allows individual users in various industries to drive insights. The study presents some constructs from the UTAUT model and tests a theory on the influence of performance expectancy, effort expectancy, social influence, and facilitating conditions, specifically focusing on the mining industry context.

Keywords: Short interval control, mining, Internet of Things, UTAUT, information technology, data visualization, Microsoft Power BI

Introduction

The drive for sustainability and the development of electric cars that use lithium and other metals has resulted in increased mining activities. To optimize operations, mining companies are implementing digital transformation technologies. It is reported that digital transformation mining impacts by 2025 will be $425 billion dollars in value, creating a reduction of 610 million tons of CO2 emissions, and improved safety with around 1,000 lives saved and 44,000 injuries avoided (Weforum, 2017). Examples of systems used by mining operations as part of digital transformation include automated short-interval control (SIC) systems. Short Interval Control (SIC) is a framework of structured processes that help identify and act on opportunities to improve the effectiveness and efficiency of mining production (GMG, 2020).

Many Mining SIC systems collect data using mobile devices. This data is streamlined and made available through data visualization tools such as Microsoft Power BI to drive better decision-making. The use of real-time information to track and monitor personnel safety, equipment, and ventilation has become more common in underground mines. With the use of sensors and Internet of Things (IoT) devices, data is captured and sent in real-time to control centers for analysis and proactive decision-making. Operational checklists and inspections are digitized and automated with humans in the loop for alerts, feedback loops, and higher risk decision-making. With all this data available in various isolated, or consolidated, data storage systems, data visualization has become an important part of the mining SIC process.

Several factors influence the acceptance and use of information technology systems such as data visualization tools. The Unified Theory of Acceptance and Use of Technology (UTAUT) is widely used to investigate the acceptance and use of technology. In this theory, user intentions to use an information system and subsequent usage behaviors are a result of four key constructs, namely performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et. al., 2003). For the purpose of this study, performance expectancy (PE) is defined as the degree to which an individual believes that using the system will help him or her attain gains in job performance (Venkatesh et al., 2003). Effort expectancy is the degree of ease associated with the use of the system (Venkatesh et. al., 2003). Facilitating conditions are the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system (Venkatesh et. al., 2003). Social influence is the degree to which an individual perceives that others believe that he or she should use the system (Venkatesh et. al., 2003).

Researchers have investigated the UTAUT (Abbas et al., 2018; Adell et al., 2018; Bhatiasevi, 2016; Cameron & Kafi, 2019; Tan et al., 2021; Zuiderwijk et al., 2015). Several studies have investigated UTAUT in different industries such as education (Alkhuwaylidee, 2019), vehicle engineering (Adell et al., 2018; Nordhoff et al., 2020), banking (Abbas et al., 2018; Bhatiasevi, 2016; Tan et al., 2021), government (Almaiah et al., 2020; Zuiderwijk et al., 2015); internet shopping (Bozorgkhou, 2015; Cameron & Kafi, 2019) and hospitality (Abbas et al., 2018). Other researchers have extended and refined the model by integrating it with other information systems models such as TAM (Technology Acceptance Model) and TTF (Task Technology Fit) (Abbas et al., 2018; Bozorgkhou, 2015; Li et al., 2020; Tan et al., 2021). However, little is researched or known on the acceptance and use of data visualization tools in mining SIC systems and effects on performance expectancy, effort expectancy, social influence and facilitating conditions within mining environments.

The purpose of the study is to investigate the impact of miners' performance expectancy, effort expectancy, social influence, and facilitating conditions on digital visualization SIC adoption. This is critical for optimizing mining operations through effective and timely decision-making, especially in mining environments where higher fuel costs, deeper ore bodies, and decreased capital investments threaten the viability of organizations still dependent on manual task execution (Weforum, 2017). Therefore, the objectives of this paper are (a) to provide theoretical grounding of the acceptance and use of data visualization technology in Mining SIC systems, (b) to briefly describe Mining Short Interval Control systems, (c) to unpack the Unified Theory of Acceptance and Use of Technology (UTAUT), (d) to discuss the effect of use and acceptance of data visualization technology in Mining SIC on performance expectancy, effort expectancy, social influence and facilitating conditions.

This paper provides three main contributions to understanding the acceptance and use of data visualization technology in mining environments. First, the effect of use and acceptance is grounded in the well-researched UTAUT. Second, an argument is if technology impacts social influence in mining environments where employees work in crews and depend on each other when capturing and using data. Third, the paper explains how data visualization technologies that have self-services and allow users to develop reports and dashboards result in the empowerment of users and bring about data governance concerns, especially if the users are not using the same data sources.

Literature Review

The UTAUT explains users' initial intentions to utilize an information system (IS) and subsequent use habits. According to the theory, use intention and behavior are directly influenced by four main constructs: performance expectancy, effort expectancy, social influence, and facilitating factors (Venkatesh et al., 2003). Venkatesh et al. (2003) explained that four main constructs of gender, age, experience, and voluntariness of use can moderate usage intention and behavior. The theory was created by reviewing and combining the eight models (theory of reasoned action, technology acceptance model, motivational model, theory of planned behavior, combined theory of planned behavior/technology acceptance model, model of PC utilization, innovation diffusion theory, and social cognitive theory) that were previously used in research to explain IS usage behavior. In longitudinal research that followed UTAUT's validation, it was discovered that these accounted for 70% of the variance in usage intention (Venkatesh et al., 2003). For this reason, Venkatesh et al. (2012) incorporated three other constructs into UTAUT: hedonic motivation, price value, and habit, extending UTAUT into UTAUT 2. The extension in UTAUT2 substantially improved the variance explained in behavioral intention (56 percent to 74 percent) and technology use (40 percent to 52 percent).

Mining Short Interval Control

As previously explained, GMG (2020) defines Short Interval Control (SIC) as a framework of structured processes that help identify and act on opportunities to improve the effectiveness and efficiency of production. The process is used as part of production optimization in both underground and open-pit mining environments. As part of the digital transformation, this business process has been automated, resulting in data from shop floor staff capturing ongoing operation data into systems that generate performance reports and dashboards to track productivity (GMG, 2020). These reports and dashboards are developed using data visualization tools and provide critical decision-making capability to middle and senior management staff in mining environments.

Short interval control, according to Wang et al. (2023), enables continuous production improvement because it allows shift management to be divided into numerous short intervals, progress control, and scheduling optimization to be conducted at each interval, and through quick progress tracking and data analysis, negative factors can be quickly identified and eliminated to increase production efficiency. Short interval control helps mining operations follow the PDCA (Plan, Do, Check, and Act) cycle, which directs future production by assessing the current condition. For example, while digging ore in a specific area, the data regarding safety hazards in the area can be captured in the mining short interval control system by the mining operator and passed on to the command center, who will see the data on the visualization dashboard and thus make a decision on whether subsequent mining should take place in that area or work should be stopped immediately.

Data Visualization Technologies

According to Unwin (2020), data visualization refers to "drawing graphic displays to show data. Sometimes every data point is drawn, as in a scatterplot, sometimes statistical summaries may be shown, as in a histogram". Klimek et al. (2012) argues that the sets of graphics are useful for providing context. Unwin (2020) supports this viewpoint by explaining that visualization is useful for data cleaning, exploring data structure, detecting outliers and unusual groups, identifying trends and clusters, spotting local patterns, evaluating modeling output, and presenting results. Because of the need to use data visualization for effective decision making and to ensure better business intelligence, there are a lot of digital visualization tools that are becoming available on the market. For example, Microsoft has developed a product called Microsoft Power BI. In our study, Microsoft Power BI was used to connect to Mining SIC systems to provide dashboards, trends, and information for users to make decisions. Microsoft Power BI is a well-regarded data visualization tool used across many industries.

Research Model and Hypothesis Development

In this study, we adapt our research model from the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) which has been widely used in similar studies such in Oil & Gas (Hawash et al., 2020), Manufacturing (Chaveesuk et al., 2023) and propose several research hypotheses that we test empirically. The research framework has been divided into user intentions to use an information system, usage behavior, performance expectancy, effort expectancy, social influence, and facilitating conditions. The antecedents are examined as the first step. Then, we propose hypotheses about the effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on digital visualization SIC adoption. Figure 1 presents the research framework adapted from UTAUT (Zhou et al, 2019).

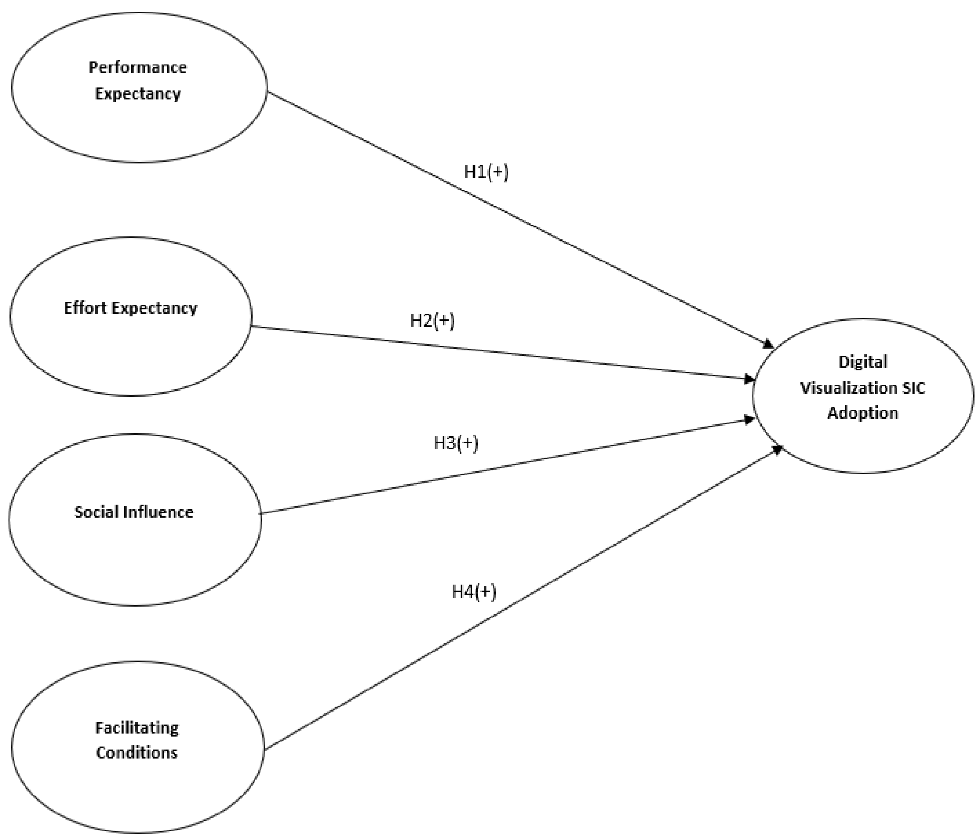

Figure 1: Research Model, Adapted UTAUT (Zhou, et al 2010)

Performance expectancy (PE) is the degree to which an individual believes that using the system will help him or her to attain gains in job performance (Venkatesh et al., 2003). Researchers have identified relationships and even empirical relationships to these related factors of adoption (Donmez-Turan, 2020; Chang et al., 2015; Zhou et al., 2010; Park et al.,2007; Alrawashdeh et al.,2012). In our study, we seek to determine if similar conclusions can be made that Performance expectancy (PE) influences the adoption of digital visualization short interval control. Therefore, we hypothesize that:

H1: *Performance Expectancy affects digital visualization SIC adoption.*

Effort expectancy is the degree of ease associated with using the system (Venkatesh et al., 2003). Researchers conducting a study on mobile banking adoption found that effort expectancy was a primary driver in user adoption of the new mobile banking technology (Zhou et al., 2010). Users were only driven by effort expectancy once there was a need to conduct transactions. The effort required to conduct mobile banking compared to walking into a physical building to conduct banking or visiting a banking website from a computer, mobile banking became the choice due to the effort expectancy of this more readily available platform (Zhou et al., 2010). In another study that drew commonalities between the effects of performance expectancy and effort expectancy, researchers in China found relationships between these two factors and the effects of the moderators of age and education on their influence (Park et al.,2007). Therefore, we hypothesize that:

H2: *Effort Expectancy affects digital visualization SIC adoption.*

Social influence is the degree to which an individual perceives that others believe he or she should use the system (Venkatesh et al., 2003). The impact of social influence on technology adoption has been widely studied and often found to be a contributing factor in adoption. Researchers studying adoption rates of web-based training systems found that adoption was heavily influenced by social influence (Alrawashdeh et al.,2012). This study aligns with our topic in that the technology being evaluated for adoption is a software platform, which would possess similar characteristics and challenges organizations face when adopting a new platform. Social influence was found to heavily influence a user's intention to use the new technology, thereby affecting their probability of fully adopting the technology. Social influence was found to have a significant relationship with the intention to adopt Electronic Records Management System (Hawash et al., 2020). Users that are in a position to adopt new technology, if they have associates, colleagues or superiors that have already been exposed to the new technology and perhaps are already adopters of the system, this will heavily influence their expectations of the products and lend to a user that is more likely to adopt. Therefore, we hypothesize that:

H3: *Social influence affects digital visualization SIC adoption.*

Facilitating conditions are the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system (Venkatesh et al., 2003). In numerous studies, it was found that facilitating conditions and social influence appeared to be related and working in concert (Park et al.,2007). In a study of web-based training systems, it was noted that these two factors heavily influenced the users ' adoption of the new system (Alrawashdeh et al.,2012). It is the case that software adoption can be viewed as an opportunity for influence by one's peers, as well as the ease of an opportunity to experiment with new technology (Alrawashdeh et al.,2012). Social influence can be seen as a facilitating condition when the social relationship is such that more opportunities for adoption become available (Donmez-Turan, 2020). Social influence was found to have a significant relationship with the intention to adopt Electronic Records Management System (Hawash et al., 2020). Therefore, we hypothesize that:

H4: *Facilitating conditions affect digital visualization SIC adoption.*

Methodology

This study was conducted to determine the impact of underground miners' performance expectancy, effort expectancy, social influence, and facilitating conditions on digital visualization SIC adoption. The specific data visualization tool used in the study was Microsoft Power BI, developed and distributed by Microsoft Corporation. Microsoft Power BI is used as an interactive visualization system and can connect to different systems and provide self-service business intelligence functionality which is a key enabler for short interval control systems (Microsoft, 2023). The research sample consisted of sixty-four (64) underground miners using the Microsoft Power BI system in an underground mine. Miners were selected to complete the questionnaire using random sampling. The sample for 64 was determined to be adequate for the effect size and power for this study using a 10-times rule method for using Partial Least Square (PLS) Structural Equation Modeling (SEM) which suggest that sample size (n) should be more than 10 times the maximum number of inner or outer model links (Hair et al., 2011;Goodhue et al., 2012;Peng & Lai, 2012). The research model in figure 1 has a maximum of 4 links and the rule of 10 would suggest n = 40 is a minimum sample size for PLS. For this reason, our sample size of 64 is adequate for analysis.

The study questionnaire was distributed among underground miners via the SurveyMonkey web-based system. An email with instructions and informed consent was sent with the questionnaire to ensure the miners were aware of the study objectives and their rights based on the research ethics. This included the confidentiality of their responses and their right to leave the survey anytime. The questionnaire was developed by adapting measures from previous studies. The measurement items pertaining to the four elements, i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions of UTAUT and user adoption, were derived from the work of Venkatesh et al. (2003).

To understand and describe the sample, we used descriptive statistics. Using SmartPLS 3.0 (Ringle, Wende, & Becker, 2015), the Partial Least Square (PLS) Structural Equation Modeling (SEM) path modeling was adopted to analyze the data and determine whether the hypotheses are supported. The study employed a two-step structural equation modeling (SEM) approach: a) assessment of the measurement model and b) the analysis of the structural model.

The study first analyzed the measurement model to test its items (factor loading), internal consistency (composite reliability and Cronbach's alpha), and construct validity. Item reliability (factor loading) showed item correlations with latent variables (Hulland, 1999). Individual item reliability examined standardized loadings. Low-loading items were deleted since they cannot contribute enough explanatory power to the model and can skew the estimations of the latent variable parameter links (Nunnally, 1978). Fornell & Larcker (1981) recommend accepting goods with loadings of 0.7 or greater as the cut-off point. A loading of 0.7 means the latent variable explained 50% of the observed variables' variance (Hulland, 1999). When scales are adapted from other settings, Chin (1998) suggests a loading of 0.5 as the cut-off point. However, items with loadings below 0.4 or 0.5 will be dropped (Hulland, 1999).

The structural model's endogenous construct prediction quality was tested. Cross-validated redundancy Q2, coefficient of determination R2, and path coefficient strength (Hair et al., 2011) achieved this. The Stone-Geiser Q2 (Geisser, 1975; Lee et al., 2011) evaluated the model's predicted accuracy (Hair et al., 2011; Hair, 2012). This determined how well the PLS-SEM model predicted the data (Hair et al., 2014). According to Hair et al. (2011), the blindfolding technique yields a nonparametric measure called Q2 with predictive relevance values greater than zero. Finally, the hypothesis was tested using the structural model's normalized path coefficients. Path coefficients also showed the strength of the constructions' direct relationship.

Research Participants

As previously stated, a total of 64 underground miners who use Microsoft Power BI participated in the study. Of the participants, 70.3% were male and nearly half (48.4%) had more than 10 years of experience. Additionally, 43.8% have not had an education beyond high school. Table 1. Participant Demographics by Sex with a specific breakdown of research participants by age group, employment category, education, and

Table 2. Participant Demographics by Sex with the breakdown of research participants by years of experience and position level.

Table1: Demographic breakdown of participants by age, employment, and education level

Demographic	Category	Sex		Opt Out	Total Participants
		Male	Female		
Age Group	22-29	7 (70%)	3 (30%)	0	10 (15.6%)
	33-39	22 (75.9%)	7 (24.1%)	0	29 (45.3%)
	>39	14 (63.6%)	7 (31.8%)	1 (4.5%)	22 (34.3%)
	Opt Out	2 (66.7%)	0	1 (33.3%)	3 (4.7%)
	Total	45 (70.3%)	17 (26.6%)	2 (3.1%)	64 (100%)
Employment Category	Hourly	25 (83.3%)	5 (16.7%)	0	30 (46.9%)
	Salary	20 (62.5%)	11 (34.4%)	1 (3.1%)	32 (50%)
	Opt Out	0	1 (50%)	1 (50%)	2 (3.1%)
	Total	45 (70.3%)	17 (26.6%)	2 (3.1%)	64 (100%)
Education	High School Diploma	22 (78.6%)	6 (21.4%)	0	28 (43.8%)
	Associate's Degree	3 (75%)	1 (25%)	0	4 (6.3%)
	Bachelor's Degree	12 (60%)	8 (40%)	0	20 (31.3%)
	Graduate Degree	5 (71.4%)	2 (28.6%)	0	7 (10.9%)
	Opt Out	3 (60%)	0	2 (40%)	5 (7.8%)
	Total	45 (70.3%)	17 (26.6%)	2 (3.1%)	64 (100%)

Table 2: Demographics of Participants by Years of Experience and Position

Demographics	Category by Selection	Sex		Opt Out	Total Participants
		Male	Female		
Years of Experience	less than 1 year	0	2 (100%)	0	2 (3.1%)
	1 to 5 years	10 (66.7%)	5 (33.3%)	0	15 (23.4%)
	6 to 10 years	8 (61.5%)	5 (38.5%)	0	13 (20.3%)
	> 10 years	25 (80.6%)	5 (16.2%)	1 (3.2%)	31 (48.4%)
	Opt Out	2 (66.7%)	0	1 (33.3%)	3 (4.7%)
	Total	45 (70.3%)	17 (26.6%)	2 (3.1%)	64 (100%)
Position Level in Organization	Top Management	0	2 (100%)	0	2 (3.1%)
	Middle Management	10 (66.7%)	5 (33.3%)	0	15 (23.4%)
	Technical Services	8 (61.5%)	5 (38.5%)	0	13 (20.3%)
	General Miner	25 (80.6%)	5 (16.1%)	1 (3.2%)	31 (48.4%)
	Opt Out	2 (66.7%)	0	1 (33.3%)	3 (4.7%)
	Total	45 (70.3%)	17 (26.6%)	2 (3.1%)	64 (100%)

Results

As discussed previously, we started our examination with the measurement model to assess the instrument's reliability and validity and then assessed the structural model to evaluate the study hypotheses. Table 3 shows the standardized item loadings, average variance extracted (AVE), composite reliability (CR), and Cronbach's Alpha scores. According to the data presented in the table, most item loadings exhibited values more than 0.7 and were statistically significant at the $p < .001$ level. The AVEs, CRs, and Alphas all surpassed the suggested threshold values of 0.5, 0.7, and 0.7, respectively (Bagozzi & Yi, 1988; Gefen et al., 2000; Nunnally, 1978). The results of this study demonstrated strong convergent validity and reliability.

The standard loadings were above 0.7, which is the minimum acceptable. Initially, a confirmatory factor analysis (CFA) was undertaken to assess the reliability and validity of the measures, specifically focusing on convergent validity and discriminant validity. The significance level for this study is either 0.01 or 0.001.

Table 3: Standardized item loadings, AVE, CR, and Alpha.

Factor	Items	Standardized Outer loadings	AVE	CR	Cronbach's alpha
Effort Expectancy	**E1**	0.964	0.88	0.994	0.935
	E2	0.906			
	E3	0.947			
Facilitating Conditions	**F1**	0.917	0.78	0.911	0.860
	F2	0.940			
	F3	0.788			
Performance Expectancy	**P1**	0.961	0.89	0.993	0.979
	P2	0.906			
	P3	0.921			
	P4	0.955			
	P5	0.914			
	P6	0.973			
	P7	0.969			
Social Influence	**SI1**	0.991	0.93	1.669	0.934
	SI2	0.934			
Digital Visualization SIC Adoption	**SICBI1**	1.000			

To perform structural modeling, we used partial least squares structural equation modeling, using Smart PLS software to perform path analysis and evaluate hypotheses. According to Gefen et al. (2000), a sample size of 64 participants is required in order to carry out the structural equation analysis given that the model has a construct with more than 5 factors. The structural equation modeling (SEM) technique employed in this study, utilizing the Smart PLS software.

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The stages were 45.7% and 43.3%, both of which exhibited a decrease compared to the previous values. In addition to employing various methodologies, we also conducted a path analysis utilizing partial techniques. Partial Least Squares (PLS) is a statistical method that is commonly used in regression analysis. Partial Least Squares (PLS) exhibit a lesser degree of restrictiveness. Regarding sample size and data dispersion, Chin, Marcolin, and Newsted (year) conducted a study that examined these factors. The expectancy and effort expectancy constructs were found to have the highest number of components, specifically four items each. Therefore, a minimum of 64 respondents is necessary in order to carry out the Partial Least Squares (PLS) analysis. The findings of the Partial Least Squares (PLS) analysis are presented in Table 5. demonstration, Table 5 presents a comprehensive compilation of path coefficients along with their corresponding levels of statistical significance, as estimated. Based on the data presented in Table 5, it can be observed that H2 and H3 hypotheses are supported.

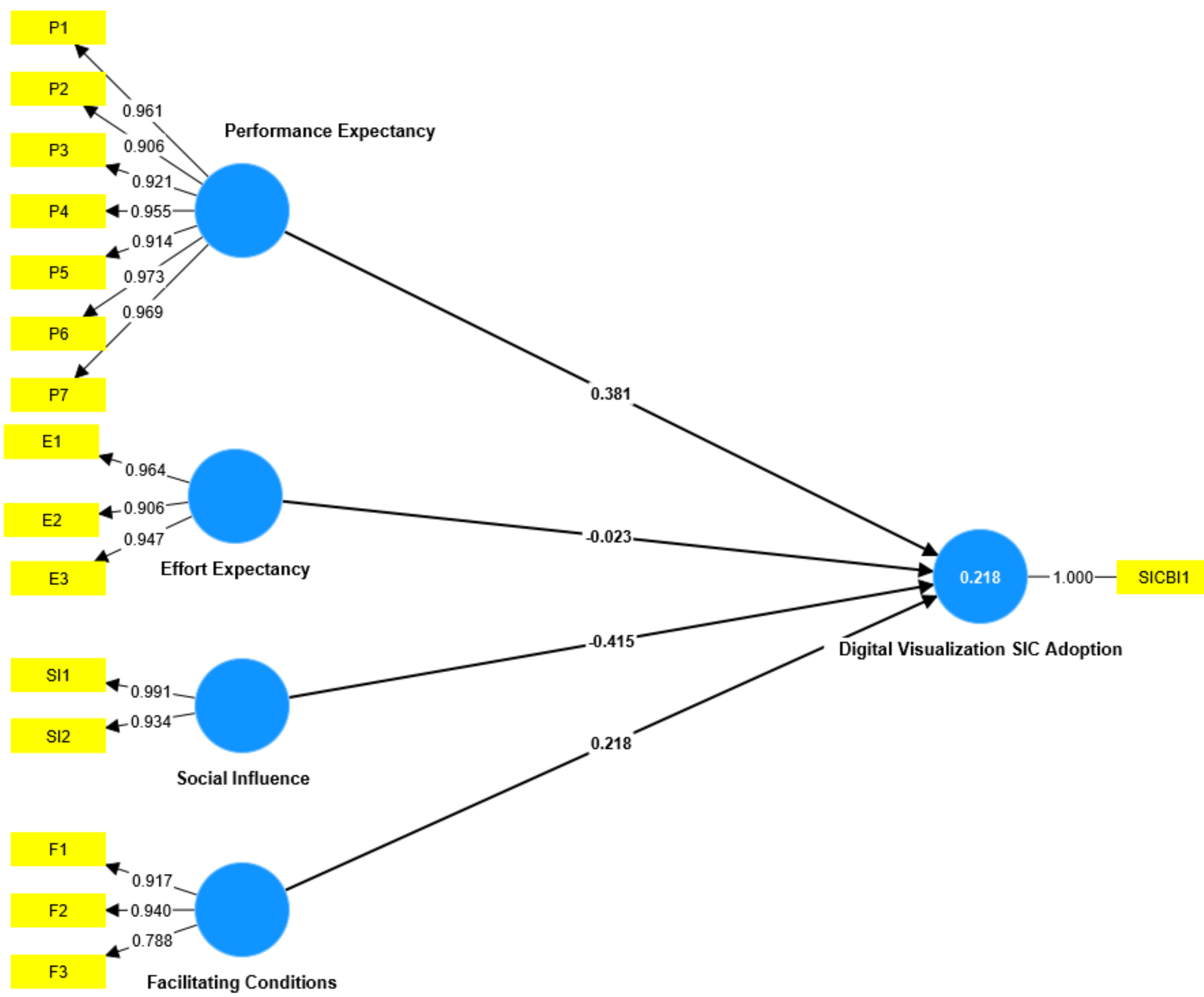

Figure 2: Model estimation results by SMART PLS

Table 4. Path coefficients and their significance

Hypothesis	Path	Coefficient	Supported or Not Supported
H1	Performance Expectancy ⇒ Digital Visualization SIC Adoption	0.38	NO
H2	Effort Expectancy ⇒ Digital Visualization SIC Adoption	-0.023 **	**YES**
H3	Social Influence ⇒ Digital Visualization SIC Adoption	-0.415 **	**YES**
H4	Facilitating Conditions ⇒ Digital Visualization SIC Adoption	0.218	NO

** $p < 0.01$.

Discussion and Conclusion

We tested a model using a questionnaire survey to understand the impacts of some of the UTAUT variables on the adoption of MS Power BI. We found that the evidence supports social influence and effort expectancy, which can support the adoption of Microsoft Power BI. Further, we found evidence that performance expectancy and facilitating conditions do not significantly impact the adoption of visual digital short interval. The study contributes to the growing knowledge of how Microsoft Power BI is being adopted in mining environments as a tool of choice for visualizations.

Our study found that performance expectancy does not affect Digital Visualization SIC Adoption, where similar studies regarding software adoption were supported, as in the electronic tax filing study, which concluded that performance expectancy had the greatest influence on adoption than all other hypotheses (Mashabela & Kekwaletswe, 2020). Another study showed evidence that a mobile health application's performance expectancy does predict acceptance among users (Apolinário-Hagen et al., 2018). In a similar study using UTAUT by Samhan (2017), the authors also investigated factors impacting software usage, in this case, it was a healthcare systems patient portal system (PPT). Their study found that Performance expectations did have a significant impact on the adoption of the PPT (Samhan, 2017).

The effects of effort expectancy in our study proved to positively impact user adoption. Similar results were obtained in a study of user acceptance of web-based training systems among public sector employees (Ibrahim & Al-Rawashdeh, 2014). In this research effort, expectancy positively impacted four hypotheses: intention, intention relationships, system interactivity, and system enjoyment. Another study on user acceptance leveraged the Task-Technology Fit (TTF) model applied to smart home technologies. The authors in this study applied TTF to the Technology Acceptance Model (TAM) and UTAUT (Marikyan et al., 2019). In this exercise, the researchers found that effort expectancy positively affected user adoption.

Social influence was the strongest predictor of behavioral intentions to use fitness wearables in a study conducted by Reyes-Mercado (2018). As in our study, social influence was one of the primary hypotheses of influence.

Facilitating conditions were not measured as influential in our study, this was also found to be the case in another research project on the acceptance and usage of mobile health apps for disease management (Apolinário-Hagen et al., 2018).

This study examined the impact of miners' performance expectancy, effort expectancy, social influence and facilitating conditions on digital visualization short interval control systems adoption. This study addresses the gap by using a unique context of underground mining where data visualization tools such as Microsoft Power BI is being used as part of short interval control systems resulting in driving insights that enables agile approaches to mining safely. Through the application of the well-researched UTAUT model, the study examined how social influence impacts data visualization tools adoptions in mining environments where employees work in crews and depend on each other when capturing and using data. Through understanding of effort expectancy study explains how data visualization technologies that have self-services and allow users to develop reports and dashboards result in the empowerment of users and bring about data governance concerns, especially if the users are not using the same data sources.

One limitation of this study was that it was conducted during Covid-19 and this resulted in many miners not participating in the study due to being out of site sick. This reduced the sample size and might impact the effect size. Furthermore, the study focused on miners from underground mining only in Nevada. Future research should be conducted in open-cast environments and possibly in other different locations with different cultures. Future research should increase the sample size to have adequate results to explain the effects and resulting generalization. Further, the studies should also be conducted in open-cast mining environments and use direct observation and logging in addition to questionnaires.

References

Abbas, S. K., Hassan, H. A., Asif, J., Ahmed, B., Hassan, F., & Haider, S. S. (2018). Integration of TTF, UTAUT, and ITM for mobile Banking Adoption. *International Journal of Advanced Engineering, Management and Science*, *4*(5), 375–379. https://doi.org/10.22161/ijaems.4.5.6

Adell, E., Várhelyi, A., & Nilsson, L. (2018). Modeling acceptance of driver assistance systems: Application of the unified theory of acceptance and use of Technology. *Driver Acceptance of New Technology*, 23–34. https://doi.org/10.1201/9781315578132-3

Alkhuwaylidee, A. R. (2019). Extended unified theory acceptance and Use Technology (utaut) for e-learning. *Journal of Computational and Theoretical Nanoscience*, *16*(3), 845–852. https://doi.org/10.1166/jctn.2019.7964

Almaiah, M. A., Al-Khasawneh, A., Althunibat, A., & Khawatreh, S. (2020). Mobile Government Adoption Model Based on Combining GAM and UTAUT to Explain Factors According to Adoption of Mobile Government Services. *International Journal of Interactive Mobile Technologies (iJIM)*, *14*(03), 199. https://doi.org/10.3991/ijim.v14i03.11264

Alrawashdeh, T. A., Muhairat, M. I., & Alqatawnah, S. M. (2012). Factors affecting acceptance of web-based training system: Using extended UTAUT and structural equation modeling. *arXiv* preprint arXiv:1205.1904.

Apolinário-Hagen, J., Menzel, M., Hennemann, S., & Salewski, C. (2018). Acceptance of mobile health apps for disease management among people with multiple sclerosis: web-based survey study. JMIR formative research, 2(2), e11977. https://doi.org/10.2196/1197

Bhatiasevi, V. (2016). An extended UTAUT model to explain the adoption of mobile banking. *Information Development*, *32*(4), 799–814. https://doi.org/10.1177/0266666915570764

Bozorgkhou, N. (2015). An internet shopping user adoption model using an integrated TTF and UTAUT: Evidence from Iranian consumers. *Management Science Letters*, *5*(2), 199–204. https://doi.org/10.5267/j.msl.2014.12.017

Cameron, B., & Kafi, A. (2019). *Investigating Consumers' Online Clothing Buying Behavior through the Lens of Extended Unified Theory of Acceptance and the Use of Technology*. https://doi.org/10.31274/itaa.8830

Chang, S., Lou, S., Cheng, S., & Lin, C. (2015). Exploration of usage behavioral model construction for university library electronic resources. The Electronic Library, 33(2), 292-307. https://doi.org/10.1108/EL-10-2013-0195

Chaveesuk, S., Chaiyasoonthorn, W., Kamales, N., Dacko-Pikiewicz, Z., Liszewski, W., & Khalid, B. (2023). Evaluating the determinants of consumer adoption of autonomous vehicles in Thailand—An extended UTAUT model. *Energies*, *16*(2), 855. https://doi.org/10.3390/en16020855 |

Donmez-Turan, A. (2020). Does unified theory of acceptance and use of technology (UTAUT) reduce resistance and anxiety of individuals towards a new system? *Kybernetes*, 49(5), 1381-1405. https://doi.org/10.1108/K-08-2018-0450

Global Mining Guidelines Group (GMG). (2020). Guideline for implementing short interval control in underground mining operations. *GMG Group*. https://gmggroup.org/wp-content/uploads/2019/06/20181015_SIC-GMG-UM-v01-r01.pdf

Goodhue, Lewis, C. K., & Thompson, D. (2012). Does PLS have advantages for small Sample size or Non-Normal data? *Management Information Systems Quarterly*, 36(3), 981. https://doi.org/10.2307/41703490

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19(2), 139–152. https://doi.org/10.2753/mtp1069-6679190202

Hawash, B., Asma, U., Mokhtar, Yusof, Z., Mukred, M., & Ali, W. (2020). Intention to adopt electronic records management system in the oil and gas sector in Yemen. *International Journal of Advanced Trends in Computer Science and Engineering*, *9*(5), 6959–6971. https://doi.org/10.30534/ijatcse/2020/13952020

Klimek, P., Yegorov, Y., Hanel, R., & Thurner, S. (2012). Statistical detection of systematic election irregularities. *Proceedings of the National Academy of Sciences*, *109*(41), 16469–16473. https://doi.org/10.1073/pnas.1210722109

Li, P., Zhou, W., & Kong, W. (2020). Research on the adoption of mobile hotel reservation based on TTF and UTAUT. *DEStech Transactions on Engineering and Technology Research*, (mcaee). https://doi.org/10.12783/dtetr/mcaee2020/35075

Mashabela, M. F., & Kekwaletswe, R. M. (2020). A model for adopting and using e-filing. *International Journal of Innovative Science and Research Technology, 5(8)*. https://doi.org/10.38124/ijisrt20aug143

Masialeti, M (2022). An empirical study of short-interval control tasks and mobile technology fit in an underground mine. *Skema Business School*. DBA Thesis

Microsoft. (2023). *What is Power BI? definition and overview: Microsoft Power BI*. What is Power BI? Definition and Overview | Microsoft Power BI. https://powerbi.microsoft.com/en-us/what-is-power-bi/

Nordhoff, S., Louw, T., Innamaa, S., Lehtonen, E., Beuster, A., Torrao, G., Bjorvatn, A., Kessel, T., Malin, F., Happee, R., & Merat, N. (2020). Using the UTAUT2 model to explain public acceptance of conditionally automated (L3) cars: A questionnaire study among 9,118 car drivers from eight European countries. *Transportation Research Part F: Traffic Psychology and Behaviour*, *74*, 280–297. https://doi.org/10.1016/j.trf.2020.07.015

Oliveira, T., Faria, M., Thomas, M. A., & Popovič, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *International Journal of Information Management*, *34*(5), 689–703. https://doi.org/10.1016/j.ijinfomgt.2014.06.004

Park, J., Yang, S., & Lehto, X. (2007). Adoption of mobile technologies for Chinese consumers. *Journal of Electronic Commerce Research*, 8(3), 196-206. https://reddog.rmu.edu/login?url=https://www.proquest.com/scholarly-journals/adoption-mobile-technologies-chinese-consumers/docview/236639894/se-2

Peng, D. X., & Lai, F. (2012). Using partial least squares in operations management research: A practical guideline and summary of past research. *Journal of Operations Management*, 30(6), 467–480. https://doi.org/10.1016/j.jom.2012.06.002

Reyes-Mercado, P. (2018). Adoption of fitness wearables. *Journal of Systems and Information Technology*, 20(1), 103-127. https://doi.org/10.1108/JSIT-04-2017-0025

Rigdon, E. E., Sarstedt, M., & Ringle, C. M. (2017). On comparing results from CB-SEM and PLS-SEM: Five perspectives and five recommendations. *Marketing: ZFP–Journal of Research and Management*, *39*(3), 4-16.

Samhan, Bahae. (2017). Patients' Resistance towards Health Information Technology A Perspective of the Dual Factor Model of IT Usage. https://doi.org/10.24251/HICSS.2017.412.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478. https://doi.org/10.2307/30036540

World Economic Forum. (2017b). D*igital transformation initiative mining and metals industry - in collaboration with accenture*. Weforum. http://reports.weforum.org/digital-transformation/wp-content/blogs.dir/94/mp/files/pages/files/wef-dti-mining-and-metals-white-paper.pdf

Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in human behavior*, 26(4), 760-767.