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# Train Your Frontline Personnel from Newbie to Master IT Users: A Three-Phase Longitudinal Experiment Focusing on Technology Compatibility

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# Train Your Frontline Personnel from Newbie to Master IT Users: A Three-Phase Longitudinal Experiment Focusing on Technology Compatibility

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## Abstract

**Background:** *Although many decision makers have recognized the importance of training to the success of their frontline personnel and organizations, hidden technological compatibility issues can lead to training failure especially when different generations, or iterations, of hardware and software are involved. In this study, we aimed to investigate the impact of different levels (high vs. low) of compatibility between software and hardware on frontline trainees' gained understanding of the related IT.*

**Method:** *Grounded in experiential learning, we designed a three-stage training experiment that involved the use of cloud-based geographical information systems and radio-frequency identification devices. The experiment included compatibility between hardware and software, a longitudinal learning simulation, and a real-world frontline scenario. 33 students enrolled in an introductory course from a major business school participated in the training, and their responses during each training stage were collected.*

**Results:** *The results revealed that compatibility is a critical factor in determining the success or failure of an IT training program. High compatibility helps frontline trainees accumulate useful IT knowledge over time, while low compatibility tends to reduce their learning outcome on the related IT over time.*

**Conclusions:** *This study is one of the few that focus on IT training issues relating to a neglected but important user group – frontline workers. Studying hardware-software compatibility of the target technology expands the understanding of factors that influence IT training outcomes. This research highlights the strategic role of well-articulated IT compatibility in frontline IT training.*

**Keywords:** IT Training, Frontline Workers, Compatibility, Experiential Learning, Longitudinal Study.

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## Introduction

As digitalization is penetrating all industries (Bughin et al., 2017), businesses have been investing heavily in information technologies (IT). A recent Gartner report projects that the global IT spending will reach 4 trillion dollars in 2021, an increase of 7.2% from 2019 (Gartner, 2020). The huge investment in IT is made not only for traditional office employees, but also for frontline workers (Barnes, 2010; Emergence Capital, 2018; Hyun et al., 2020).

Frontline workers are professionals, such as salespeople, healthcare providers, housekeepers, technicians, construction laborers, and production line workers, who primarily spend their time on customer-facing or operational activities (Gartner, 2019; McBride et al., 2005). These workers account for 80% of the global workforce, or about 2.7 billion people (Emergence Capital, 2018). It is estimated that 30% of total mobile and endpoint budgets in 2020 was devoted to frontline workers' needs, and up to 70% of new investments in mobile and endpoint net will be aimed at frontline workers between 2021 and 2024 (Gartner, 2019). Practitioner reports show that scaling IT investments to frontline workers can increase efficiency while enhance customer satisfaction and product or service quality (Harvard Business Review Analytic Services, 2017), eventually delivering bottom-line growth to organizations (Forbes Insights, 2017). To realize these desired benefits, a number of organizations have started to train their frontline workers to develop and apply new IT skills and thus fully exploit technologies as part of their daily routines (Avgar et al., 2018; Habjan et al., 2014; Shibl et al., 2013; Venkatesh et al., 2011). For example, 50% of highly digital firms were reported to offer their frontline workforces proper training whenever a new technology was introduced. Moreover, some firms started to incent their management to encourage frontline workers to take advantage of training of new technologies (Harvard Business Review Analytic Services, 2017).

Despite the efforts of promoting training to frontline workers, a report reveals that 41% of frontline workers believe that their workplace training in general is ineffective (Axonify, 2019). One of the top reasons for ineffective training is that the provided training does not help frontline workers perform their job. To address this problem, numerous academic studies have investigated how to improve training for frontline workers (e.g., Edinger-Schons et al., 2019; Jakobsen et al., 2019; Shah, 2021). However, studies have focused primarily on general training context rather than IT training in particular. IT receives limited attention from the frontline worker training field because organizations traditionally tend to implement IT for their back-office employees, such as IT professionals (Forsgren et al., 2016) and ERP system users (Kwak et al., 2019). Recently, as demonstrated in the aforementioned industry reports, an increasing number of organizations have begun investing in IT to support the jobs performed by frontline employees. As IT training plays a vital role in realizing desired business returns from IT investments (Atasoy et al., 2021; Mehra et al., 2014), it is imperative for scholars to examine IT training of frontline workers and evaluate its effectiveness. In fact, the job performed by frontline workers usually involves the use of both hardware and software. For instance, applications embedded in tablets or smartphones need to work with handheld printers if direct store delivery drivers need to print in the field. Drones must cooperate with drone mapping software so that operators can collect intelligence from any job site. Therefore, during training, frontline workers need to learn how to interact hardware with software in order to perform tasks. When a task requires the cooperation between hardware and software, their compatibility tends to be an issue. Compatibility between software and hardware (we use compatibility thereafter) refers to the degree of integration between software and hardware so that software programs work together with hardware devices (Hu et al., 2003; Tan & Chou, 2008). Poor compatibility can lead to adverse scenarios such as disappearing features, slow running systems, and system malfunctions (Beta Breakers, 2016). These scenarios not only can discourage frontline workers from using the related IT (Ali et al., 2020; Driscoll et al., 2019; Yoon et al., 2020) but also can harm their job performance at large (Liu et al., 2020). Thus, compatibility should be an important factor influencing the success of an IT training program


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and the thereafter frontline work. However, the existing research interested in training outcome has only included trainees' cognition and training context as antecedents (De la Torre et al., 2016; Zhu et al., 2019) while overlooking important technical factors such as compatibility. This is the first research gap.

The other gap is that the current frontline IT training research tends to rely on cross-sectional research design and has not explored the longitudinal approach. Longitudinal approach can be especially important because an IT training program typically involves multiple sessions over the course of several weeks (Brown et al., 2019). As trainees immerse in their training programs more, their understanding of the target technology also develops (Lee & Xia, 2011; Luse et al., 2013). By taking the time factor into account, we can garner a richer comprehension of the focal factors in the formation of trainees' understanding of IT. To bridge these research gaps, we study the following research question: How does the compatibility between software and hardware of the target technology influence trainees' understanding of the technology over time?

Grounded in experiential learning (EL), a three-stage experiment that involves the use of cloud-based geographical information systems (GIS) and radio-frequency identification (RFID) devices is designed to answer the research question. The findings are interesting: when compatibility is high, trainees' understanding of the target technology increases over time; when the compatibility is low, trainees' understanding decreases over time. Our study makes contributions in five aspects. First, this study is one of the few focusing on IT training issues relating to a neglected but important user group – frontline workers. Second, we expand the understanding of factors that influence IT training outcomes by studying hardware-software compatibility of target technology. Third, our study is the first longitudinal study in the frontline IT training context. Fourth, we extend the application of EL and introduce a useful framework into the design of IT training for the front lines. Lastly, our findings provide valuable insights for Human Resources and Learning & Development leaders with regard to delivering effective IT training programs for frontline workers.

The remainder of this article is structured as follows. We first present a literature review on IT training for frontline workers, EL, and the framework of computer faculty. Next, we describe the experimental design and data collection. Then, we illustrate data analysis and present our results. We close with a discussion as to how our research contributes to theory and practice.

## Literature Review

### *IT Training for Frontline Workers*

IT training is defined as "a planned activity that can help workers obtain predetermined levels of knowledge and skills in IT" (Santhanam et al., 2013, p. 136). IT training research has paid considerable attention to back-office workers such as employees working with ERP systems (Kwak et al., 2019; Söllner et al., 2018), IT professionals (Fang et al., 2011; Forsgren et al. 2016; Lee & Xia, 2011; Mehra et al., 2014), and business professionals (Luse et al., 2013; Montoya et al., 2010). The missing piece in this body of research is the adequate knowledge on training for frontline IT users.

Although still limited, the extant studies on frontline IT training have started to elucidate the importance of training at the front lines to organizations. For example, evidence has revealed that providing training for frontline workers not only facilitates the adoption of technical tools in their daily routines (Lee et al., 2019) but also improves organization's IS-generated benefits (Atasoy et al., 2021; Avgar et al., 2018; Habjan et al., 2014; Shibl et al., 2013; Venkatesh et al., 2011). Because frontline IT training appears to be beneficial, designing sound training programs becomes naturally vital. A few researchers investigated the influence of trainees' cognitive aspects (De la Torre et al., 2016) and training contexts (Zhu et al., 2019) on training results. However, there is a lack of knowledge on the effect of technological factors on training outcomes. Prior studies observed that technological issues (e.g., incompatibility in technologies) result in difficulties in implementation (Lee et al., 2020), adoption (Soon & Gutiérrez, 2010), and actual use of IT (Liu et al., 2020; Matt et al., 2019). In a similar vein, IT training without key technological components properly implemented can also lead to consequences that will occur after the training. As such, it is imperative to understand technological factors that can contribute to or impede frontline IT training outcomes.

Compatibility between software and hardware is a technological factor that is often overlooked especially by untechnical decision makers. Frontline work often requires compatible software and hardware, which should be implemented sufficiently in the corresponding training sessions. In fact, compatibility issues in frontline work started to receive attention outside the IT training research. For instance, establishing compatibility between software and hardware platforms has been found to be one of the top factors that drive the success of IT adoption by healthcare professionals (Driscoll et al., 2019), shopfloor workers (Kürschner et al., 2010), farmers (Yoon et al., 2020), and public administration frontline workers (Ali et al., 2020). Due to the lack of research that focuses on technology compatibility issue in the IT training field, understanding how software-hardware compatibility impacts frontline IT training outcomes makes important contributions to the rooted literature.

Another issue revealed in the literature of frontline IT training is the lack of diversity in methods, restricting the potential insights to be generated through the available resources. The majority of the studies on frontline IT training used cross-sectional data rather than longitudinal data (Avgar et al., 2018; De la Torre et al., 2016; Habjan et al., 2014; Shibl et al., 2013; Zhu et al., 2019). Yet, learning a new IT (or anything else) is a process. Thus, observing and predicting changes in training outcomes through cross-sectional designs is not ideal (Silic & Lowry, 2020). Additionally, training outcomes, such as trainees' understanding of a target IT, are likely to change over time as trainees learn more about the related technology (Lee & Xia, 2011; Luse et al., 2013; Zhang et al., 2011). Lastly, most training programs consist of multiple training sessions. One-time snapshots of training outcomes provide an incomplete picture of IT training because the outcomes may vary across sessions (Gupta & Bostrom, 2013). Therefore, it is necessary to employ longitudinal design in frontline IT training to understand whether and how training outcomes change over time. In this study, we take an exploratory approach and implement a longitudinal experiment to understand the impact of compatibility between software and hardware on trainees' understanding of a selected technology. Based on the existing but limited studies related to our research, we expect that, in general, a good level of compatibility can promote desirable training outcomes among frontline IT users. The detailed impact that is time sensitive is expected to be revealed by our experiment through an underlying learning model.

### Experiential Learning and the Theoretical Framework of Computer Faculty

Experiential learning takes place when "a personally responsible participant cognitively, affectively, and behaviorally processes knowledge, skills, and/or attitudes in a learning situation by a high level of active involvement" (Hoover & Whitehead, 1975, p.25). EL is a critical educational model that facilitates individuals' learning outcomes through simulations or real-world experiences (Burch et al., 2019). This learning model is broadly used in student education studies, such as teaching engineering (Hajshirmohammadi, 2017), management (Tomkins & Ulus, 2016), and health courses (Grace et al., 2017). Because EL is continuously considered a major approach in improving learning outcomes, researchers interested in employee training started to incorporate EL into their studies, including some focusing on the front lines. Such examples can be found in a review on training primary healthcare workers by Chamane et al. (2019) and a review on training newly licensed nurses by Warnke and Thirlwell (2014).


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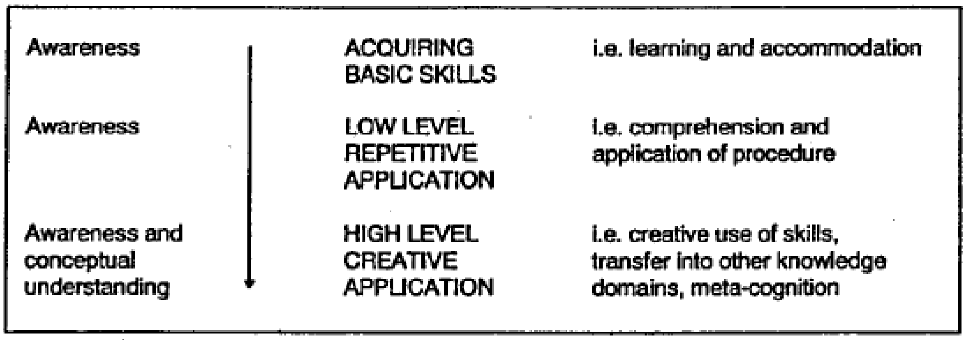
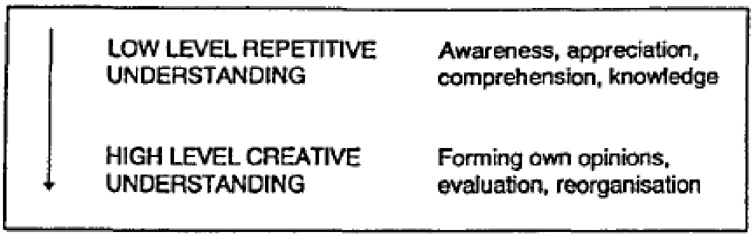
Within the literature of EL, we identified Selwyn's (1997) theoretical framework of computer faculty as a suitable guide for designing our study. Computer faculty is described as "the learner's overall use and understanding of computer technology" (Selwyn, 1997, pp.52). In other words, computer faculty refers to someone's overall capability with computer information technology. Learning is the innate process to gain computer faculty. Based on Selwyn's framework, a learner's computer faculty is formed through an ongoing development process with two dimensions: (1) computer expertise and (2) computer understanding (demonstrated in Figure 1). Computer expertise refers to the technical skills of computer use (e.g., controlling the computer, entering, organizing, manipulating, and modeling data). Computer expertise follows a progression through three stages: acquiring basic skills, low-level repetitive application of procedures to reinforce skills, and high-level creative application during which a learner is able to apply skills to other contexts. Computer understanding encompasses a critical evaluation of the computer technology, for example, its advantages, limitations, social impacts, and appropriateness in different contexts. Alongside the progression of technical skills, the understanding of that particular application of computer technology is progressed from low-level repetitive understanding to high-level creative understanding.




(a) Model of progression of computer expertise




(b) Model of progression of computer understanding

**Figure 1 - Selwyn's (1997) computer faculty framework**

Since the framework of computer faculty describes the progression of computer expertise and the progression of computer understanding along the development of computer expertise, this framework can help us design a longitudinal experiment. The three-stage progression of computer expertise enables us to determine the number of experiment stages and tasks performed in each stage. The experiment in our study involves three stages, with tasks respectively focusing on basic skills, repetitive application, and creative application. Such experimental design allows us to evaluate the pattern of trainees' understanding of IT along the progression of computer expertise.

## Methodology and Analysis

### *Experiment Design*

To answer the research question, we implemented an experiment of a cloud-based GIS training, which includes compatibility between hardware and software, a longitudinal learning simulation, and a real-world frontline scenario. We expect that investing in hardware-software compatibility is especially crucial to the formation of positive understanding of IT at the front lines.

We designed this experiment by recruiting students at a land-grant university in the south of the U.S. All the hardware and software required for this experiment were provided by a local GIS equipment firm. Students were selected because they closely resembled "the population of interest … on theoretically relevant variables" (Gordon et al., 1987). It is suggested that students are appropriate for business-focused laboratory experiments if they possess "a shared past and expected future" (Lee & Dennis, 2012, p. 23) of the human subjects of interest. In regard to IT use, these students are in the generation who has learned how to use computers, portable devices, and different computer applications, and will be learning new information technologies and systems as their jobs or lives require. In the experiment, students were requested to handle certain IT from a frontline trainee's perspective in the blue-collar industry. In the questionnaire distributed at the end of each experiment phase, students were asked to answer questions in regard to their understanding of the selected IT in their tasks. Thus, these individuals "enact a world in front of the text" (Lee & Dennis, 2012, p. 23).

This experiment was designed based on two considerations: the underlying framework and operational measures. First, to ground the study design properly in the EL, Selwyn's (1997) framework was adopted. Because our main focus was to compare the effect of compatibility on students' GIS learning, we tended to maintain parsimony in the framework. Thus, we decided to combine the computer expertise and computer understanding layers into a three-stage computer faculty framework against which we designed a three-phase GIS learning experiment. Figure 2 (a) depicts the parsimonious model of Selwyn's framework, while Figure 2 (b) elucidates our three-phase model for the cloud-enabled GIS training experiment based on the parsimonious framework.

Prior to the three-phase experiment, thirty-three student volunteers were recruited. Proper locations were also selected for those phases to take place. A regular classroom and a computer lab were arranged for Phase 1and Phase 3, respectively. For Phase 2 (i.e., field work), two similar but separate locations were used to create treatment group and control group for the data analysis in the next section. The idea is that when an IT enabled task requires both hardware and software, compatibility between hardware and software is critical for user performance (Wilen et al., 2003). High compatibility can be assured by the latest version of both hardware and software, but the same level of compatibility may not be maintained when up-to-date software is assigned to work with an older generation of the hardware. Thus, an on-campus location was selected to host the treatment group. The research team buried 44 RFID geo markers along the selected water lines and electric lines at this location about two months prior to this experiment. These RFID tags were the latest version provided by the local GIS firm. The research team also identified an off-campus location where the local utility buried 48 RFID markers about two years before our experiment. Supplied by the same company, these geo tags were an older product generation. To create variation in compatibility, the latest version of the required software was installed for both fields. Based on our design, the treatment group (high compatibility) would take place in the on-campus location where the latest version of both hardware and software was provided. The control group (low compatibility) would conduct tasks in the off-campus field to which older generation of the hardware and new version of the software were assigned. These two outdoor locations were similar in terms of area, layout, traffic condition, and other factors to eliminate the unwanted influence generated by the environmental variation. This helped us focus on the impact created by different levels of compatibility between hardware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and software. Appendix A depicts the required tools and the application of these tools for the GIS projects.

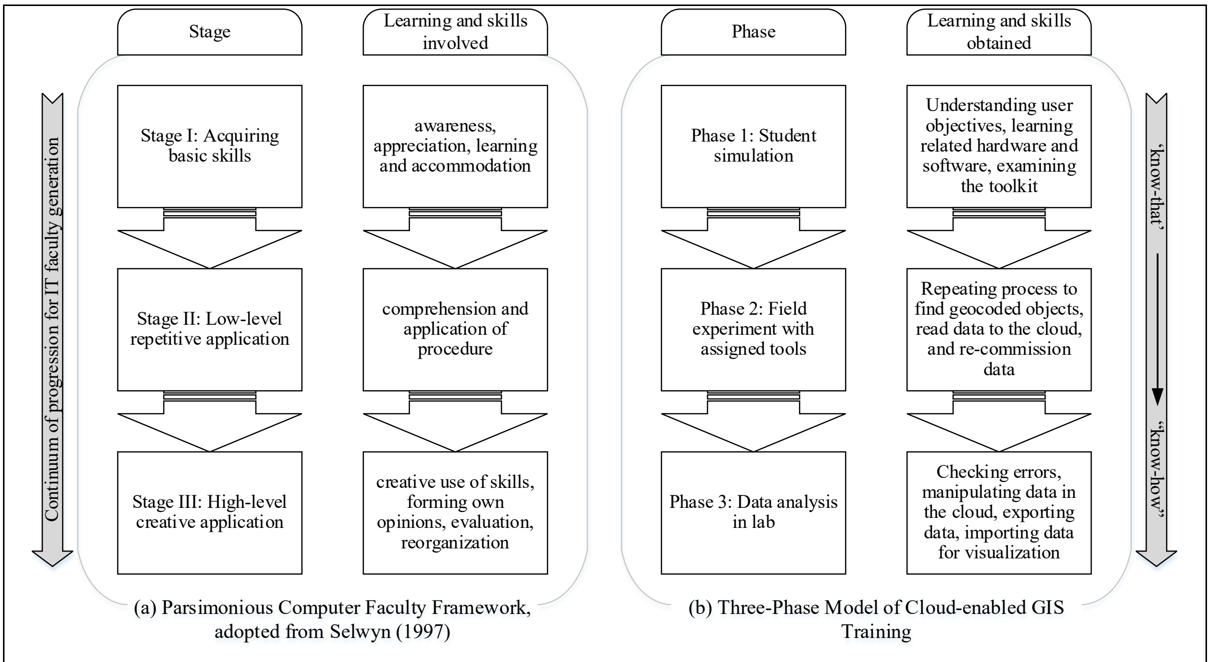


**Figure 2 - Three-phase model of cloud-enabled GIS training adopted from Selwyn (1997)**

In Phase 1 – Student Simulation, trainees gained basic GIS and cloud computing skills through a demonstration on the concepts and applications of these technologies and an initial self-exploration of the target equipment and software (toolkit) used in the experiment. To facilitate an effective learning environment, several videos were played to illustrate the application of the toolkit in real scenarios. In Phase 2 – Field Experiment, trainees' GIS skills were reinforced through continuously locating buried RFID markers and reading/writing their information into the cloud-based servers through the corresponding mobile app. Eighteen students were selected randomly to work at the on-campus location, while the remaining 15 individuals were assigned to the off-campus site. During this phase, students were expected to conduct repetitive procedures to locate geo tags and re-commission data through interacting with the cloud-based mobile app. Such activity provided these "newbies" an opportunity to generate first-hand knowledge on the usefulness of cloud computing and the ease of use of the application for their on-going tasks. In Phase 3 – Data Analysis, student trainees were required to conduct data analysis tasks. In particular, students were heavily engaged in identifying errors in their data, inputting additional information to reduce missing data, exporting data into a different format (.csv), and importing data into Google Maps website for data visualization. Based on their data activities in this phase, students also discussed different scenarios that the data can be used in the future. Because this lab session relied significantly on cloud computing, students' IT faculty on cloud computing is expected to be further developed towards the "know-how" level. Creative use of cloud technology is sprouting and developing among the trainees. Appendix B helps visualize these three phases via photos.

Second, a questionnaire was developed to check students' gained understanding on cloud-enabled GIS. In our GIS training, cloud computing was an essential technological foundation that supports the real-time geocoding, tracking, storing, and manipulating asset data. Cloud technology was also explicitly and progressively demonstrated for student trainees over the three phases. Thus, we designed a questionnaire (see Table 1), based on a 5-point Likert scale, to understand these trainees' training outcome at the frontline. The responses after Phase 1 were set as the baseline. When all three phases along with the questionnaires were completed, a longitudinal (panel) data set was generated for the quantitative analysis.

| Table 1 - Questionnaire | | |
|---|---|---|
| **No.** | **Question** | **Loading** |
| 1 | I know the application of cloud computing well. | 0.714 |
| 2 | Cloud computing is useful to frontline workers. | 0.885 |
| 3 | Cloud computing can boost frontline workers' productivity. | 0.912 |
| 4 | Cloud computing can increase the accuracy of frontline workers' work deliverables. | 0.891 |
| 5 | Cloud computing can reduce work complexity for frontline workers. | 0.839 |
| 6 | Cloud computing can make frontline workers' work more effective. | 0.873 |
| 7 | Cloud computing can help frontline workers collaborate online without generating paper-based documents. | 0.801 |
| 8 | Cloud computing can make frontline workers' job more flexible. | 0.843 |
| 9 | Cloud computing can make frontline workers' job more reliable. | 0.840 |

## Data Analysis and Results

The recruited students were enrolled in an introductory level IS course. Participation was not mandatory, and extra credits were issued to each participant. Our final sample contained 33 students. Of those 33 individuals, 11 were female (33.33%), and 22 were male (66.67%). 25 were business related majors (75.76%), and 8 were engineering related majors (24.24%). The average GPA was 2.97, with 1 student's GPA below 2, 22 students' between 2 and 3, and 10 higher than 3. After the three-phrase study, 99 data instances were collected for our panel data analysis. Due to one student drop in phase 3, 98 usable data instances were kept.

## Variables

Training outcome (student trainees' gained understanding on cloud computing technology) is measured by the nine questions in the questionnaire. High IT compatibility is a binary independent variable. We designed a treatment group and a control group to test IT impact on trainees' learning outcome. The treatment group contains those who conducted the field phase at the on-campus location by using the new version of both the hardware (RFID geo tags) and software (mobile app and geo tag reader/writer). The control group includes individuals who finished the field work at the off-campus site using a combination of the older version of the hardware and the new version of the software. High IT compatibility equals 1 if the subject is in the treatment group; the value is 0 if the subject is from the control group. Phase is an independent variable representing three different time points in the study. It takes a value among 1, 2, and 3. Besides, students' gender and GPA are included as control variables. Table 2 depicts the operational definition and descriptive statistics of all the variables involved in the model. Table 3 displays the correlations between the variables.

## Measurement Model Assessment of Dependent Variable

Since training outcome (trainees' gained understanding of cloud computing technology) is a latent variable, the measurement model was evaluated to check the reliability and validity of the measures. A construct is considered reliable if its Cronbach's alpha exceeds 0.7 (Cronbach & Thorndike, 1971) and composite reliability (CR) is greater than 0.8 (Chin, 1998). The Cronbach's alpha and CR of training outcome are 0.95 and 0.96 respectively, thus satisfying the suggested reliability thresholds. We assessed measurement validity in terms of convergent validity. Convergent validity was evaluated using item loadings and average variance extracted (AVE). The loadings of all the measurement items (see Table 1) exceed the cutoff value 0.6 (Anderson & Gerbing, 1988). The AVE is 0.72, greater than the cutoff value 0.5 (Fornell & Larcker, 1981). Therefore, convergent validity is satisfied. Discriminant validity is not applicable in this paper because we only have one latent construct. In summary, the measurements of the dependent variable carry sound reliability and validity necessary for further data analysis.


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| Table 2 - Definition and descriptive statistics of the variables (N = 99) | | | | | |
|---|---|---|---|---|---|
| **Independent and control variables** | **Description** | **Mean** | **S.D.** | **Min** | **Max** |
| Gender | A binary variable, taking the value of 1 if the student is a female and 0 otherwise. | 0.333 | 0.474 | 0.000 | 1.000 |
| GPA | Student GPA ranging from 0 to 4. | 2.970 | 0.974 | 1.000 | 4.000 |
| High compatibility | Students were randomly assigned to one of the two fields. On-campus field was featured by the combination of new geo tags and new software; off-campus field was associated with the combination of older geo tags and new software. High compatibility is a binary variable, taking the value of 1 if the student was assigned to the on-campus field and 0 otherwise. | 0.545 | 0.500 | 0.000 | 1.000 |
| Phase | A time indicator with value 1, 2, or 3. There were three phases involved in the experiment. | 2.000 | 0.821 | 1.000 | 3.000 |
| **Dependent variables** | **Description** | **Mean** | **S.D.** | **Min** | **Max** |
| Training outcome* | The average training outcome based on the nine questions on the questionnaire. | 4.171 | 0.736 | 2.111 | 5.000 |

* The number of observations for this variable is 98, indicating 1 missing data entry.

| Table 3 - Correlation matrix | | | | |
|---|---|---|---|---|
| | Gender | GPA | High compatibility | Phase |
| Gender | 1.00 | | | |
| GPA | 0.09 | 1.00 | | |
| High compatibility | 0.00 | 0.10 | 1.00 | |
| Phase | 0.00 | 0.00 | 0.00 | 1.00 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

### *Statistical Model*

Because the data were collected in a longitudinal design, we expected the responses within the participants to be correlated with each other over time. In addition, this panel data set is unbalanced due to the missing value generated by a participant's drop during the third phase. Thus, generalized estimating equations (GEE) is selected over ordinary least square (OLS) and repeated measures ANOVA (Liang & Zeger, 1986; Zeger & Liang, 1986).

GEE with an exchangeable correlation structure was adopted to address any potential bias. In particular, bias from clustered samples (rather than simple random samples) can arise when respondents are randomized at the cluster (participant) level, but analyzed based on conventional regression analysis (OLS). Analyses that do not take this clustering into account may report significance erroneously, that is, accounting for clustered samples as multiple simple random samples can inflate statistical probability of significance (Agresti, 2007). Stated differently, similarities among responses from the same student (i.e., cluster) or from those who share a natural cluster can reduce the total variation among questionnaire responses compared to that expected from a random sample. In most cases, the empirical results from clustered samples may result in an overestimation problem and generate smaller p-values simply because of the similarities among responses. To verify our concern on potential clustering issues in the data, we first created a Spaghetti plot (Allen, 2010) to visualize individual responses at each phase (see Figure 3) as these responses may be an indicator of the underlying clustering situation. During the first phase, the responses are near evenly distributed, with several data points clustered around 4.5 for training outcome. The clustering becomes more apparent during the second and third phases. For example, for training outcome of phase 2, a number of responses are clustered near 5, a group of data points are surrounding 4, and some others are near 3. The pattern further changes in phase 3 in which more data points are between 4 and 5 and some scatter below 3. In addition, we also identified that some students share the similar training outcome trend over the entire experiment. Although identifying the causes of these phenomena was out of the scope of this research, bias could be introduced due to unknown characteristics, or clusters, shared among these students. Thus, it is necessary to handle potential biases caused by clustering via data analysis.

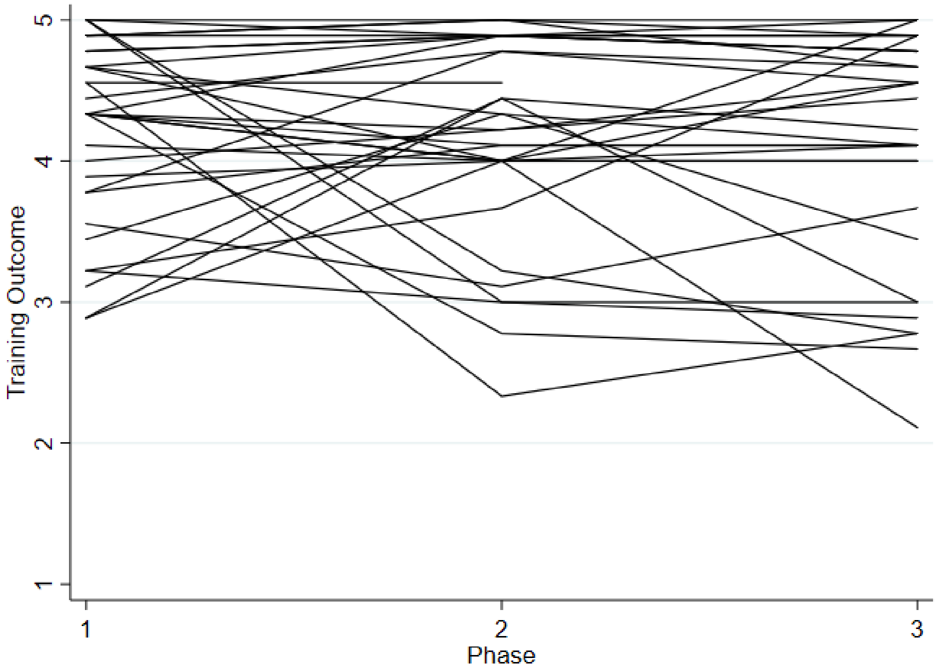


**Figure 3 - Spaghetti plot of training outcome for each individual during three phases**

To cope with the potential biases, appropriate clusters were included in the GEE modeling. These clusters were participants within both treatment group (high IT compatibility) and control group (low IT compatibility). We also adopted the GEE with the exchangeable correlation matrix that uses the estimated Pearson residuals, $\hat{r}_{it}=(y_{it}-\hat{\mu}_{it})/\sqrt{V(\hat{\mu}_{it})}$, from the current fit of the model to estimate the common correlation parameter. Further, our empirical test relied on the test statistics and their associated p-values. We used robust standard errors (typically larger than non-robust standard errors) that are robust to heteroscedasticity or unequal variables.

Before the GEE analysis, we ran a t-test to check if GPA is different between the treatment and control groups. The results ($t = .543$, $p = .591$) indicate no significant difference between these two groups.


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## Results

We used Stata (version 15) for our data analysis. The main effect model (Table 4, column 1) shows that, compared with low compatibility, high compatibility plays a significant supportive role in frontline worker training (β = .53, $p < .01$).

**Table 4 - Focus group participants background classification**

| GEE model | (1)<br>Main effect | (2)<br>Interaction effect |
|---|---|---|
| Gender | 0.026 | 0.030 |
| | (0.177) | (0.177) |
| GPA | 0.004 | 0.007 |
| | (0.089) | (0.088) |
| High compatibility | **0.530***** | -0.212 |
| | (0.180) | (0.336) |
| Phase | -0.064 | **-0.271*** |
| | (0.087) | (0.158) |
| High compatibility × Phase | | **0.373**** |
| | | (0.174) |
| Constant | 3.988*** | 4.390*** |
| | (0.302) | (0.388) |
| Observations | 98 | 98 |
| Number of StudentID | 33 | 33 |

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

After adding the interaction term (high compatibility × Phase), we investigated whether compatibility level plays a role in trainees' gained understanding on IT over time, i.e., whether high compatibility (treatment group), compared with low compatibility (control group), in IT use leads to a better learning outcome during the course of training. In this GEE model (Table 4, model 2), the coefficient of high compatibility contributes to different intercept between the treatment and control groups. The coefficient of phase in the treatment model and the control model represents the corresponding slope of the model. High compatibility group and low compatibility group are drastically different from each other based on the analysis results and the regression plot (Figure 4). These two coefficients uncover the following results. First, the coefficient for high compatibility (β = -.212), i.e., the estimated difference in intercepts, is very small (4.178 for treatment vs 4.39 for control). Because the intercepts are defined as the average score at the baseline phase (phase 1), this result indicates that although these two groups have different intercepts and slopes, the average scores at the beginning of the experiment did not vary significantly. This makes sense because the two levels of compatibility were not involved until phase 2 (field phase). The similar average scores at phase 1 mean that the initial group randomization of the subjects was carried out properly. Second, the estimated difference in slopes (β = .373, $p < .05$), i.e., the interaction term, is highly significant, indicating that student trainees' gained understanding increases over time more quickly for the treatment group than for the control group. This fact is further demonstrated in Figure 4. The learning outcome, which is reflected by students' responses in the questionnaire, actually decreased over the course of training because of low compatibility.

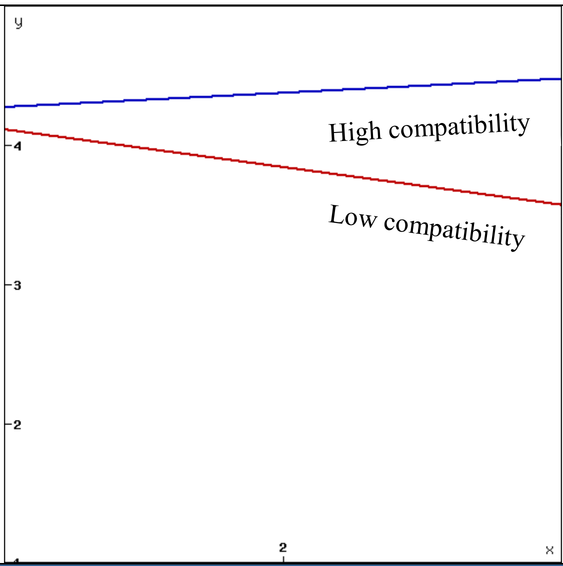


**Figure 4 - Student response during the course of training by group**

## Discussion

Frontline personnel represent an important and large group of individuals working in the front lines of such sectors as agriculture, manufacturing, construction, transportation, and healthcare (Emergence Capital, 2018). These workers usually need sufficient amount of knowledge on both hardware and software due to the deep penetration of IT in both public and private sectors. Thus, both for-profit and not-for-profit organizations need to provide effective training to secure their work quality and productivity at the front lines. However, the extant literature of IT training lacks knowledge on training frontline personnel. To fill in this research gap, we answered an important question through this study: how does the compatibility between software and hardware of the target technology influence trainees' understanding of the technology over time? Through a three-phase experiment of training university students to use GIS and cloud computing technologies, we looked into IT learning (training) outcome enabled by high/low levels of hardware-software compatibility. In other words, we split our student volunteers into a treatment group assigned with high compatibility and a control group assigned with low compatibility. With their assigned compatibility level, participants were trained to manage cloud computing supported equipment to locate important community subterranean assets (e.g., water lines, electronic lines). At the end of each phase during the experiment, we asked these students to rank their level of agreement relating to the influence of cloud computing technology on the daily work of frontline utility workforce. Our longitudinal analysis revealed how well the software and hardware work with each other determines the final training outcome. To answer our research question explicitly: when no significant difference exists in personnel's learning capability and initial understanding on the selected IT between the treatment and control groups, higher level of software-hardware compatibility accelerates trainees' learning outcome overtime.

### *Contributions*

This study makes several implications for both theory and practice. First, we contribute to the literature of IT training. Despite a population of about 2.7 billion (Emergence Capital, 2018), frontline workers are not well represented in the IT training literature. Our study focuses on this important user group and addresses research gaps and opportunities in this area in two respects. The first respect is that we contribute to an expanded understanding of factors that influence IT training outcomes by examining the role of hardware-software compatibility of the target technology. Although compatibility is an important driving force of the adoption of new (generational) technologies (e.g., Ali et al., 2020; Driscoll et al., 2019; Kumar et al.,, 2017; Lee et al., 2020; Liu et al., 2020; Matt et al., 2019; Tripathi & Mishra, 2019; Yoon et al., 2020), it has been largely overlooked in the context of IT training. Our study focuses on this neglected element and provides empirical support for the positive effect of compatibility on trainees' gained understanding of cloud computing technology. This finding also further extends the literature of compatibility by studying it in a new context (i.e., IT training) and linking it with an important training outcome (i.e., the gained understanding of new technology). The second respect is that we are the first to use a longitudinal study in the frontline worker IT training context. Longitudinal study approach has been used in the research on IT training for office workers (Luse et al., 2013; Silic & Lowry, 2020) and for students (Gupta & Bostrom, 2013; Kher et al., 2013). A consistent finding from such research is that longitudinal data enable researchers to observe change trajectories in training outcomes over time. Our finding is in line with previous long-term studies on non-frontline worker IT training because clear change pattern in trainees' understanding of cloud computing is seen in both control and treatment groups (Figure 4). This finding will encourage researchers to incorporate time element in exploring factors that influence frontline workers' IT training outcomes.

Second, this study extends the use of EL into the setting of IT training for frontline workers. The results of our experiment confirm the effectiveness of EL-supported training design in facilitating frontline workers' learning outcomes on technologies. Scholars interested in research on frontline workers' IT training may adopt experiential learning as the theoretical base for study design. Additionally, we re-adjust Selwyn's (1997) framework into a parsimonious model and apply it to our longitudinal experimental design. Experiential learning is widely discussed in the context of student learning but not so much in training. Through the parsimonious model, we are able to examine trainee's learning from a longitudinal perspective. Future studies trying to probe trainees' learning over time can utilize this parsimonious model as a basis for the design of longitudinal experiments. We are able to closely examine training from a more cognitive perspective. In other words, IT related training, especially for onboarding, requires that the learners be engaged with the appropriate tools and methods based on cognition and learning processes.

Third, this study provides implications for organizations that are investing in IT for frontline workers and seeking effective means to equip them with required skills through training. IT training is not always about software. When taking both hardware and software into consideration, we found that well integrated hardware/software system contributes to better simulation (training) outcomes. Budget constraint is the leading obstacle to technology deployment to frontline workers (Forbes Insights, 2017). When it comes to cost, investing in hardware and its upgrades can cost more than the investment for software (Farias, 2018). As such, organizations may not invest in hardware timely. However, developers constantly update their software applications, which may lead to compatibility issues if matching hardware is necessary. In this case, lowering budget on hardware, delay in hardware upgrade, or exclusion of older hardware versions in the matching software design will lead to low hardware-software compatibility which causes errors and confusion in the worker's tasks. We suggest that organizations check the hardware-software compatibility before conducting their training programs.

### *Limitations*

Nevertheless, several limitations exist in this research. First, IT training literature suggests that training needs to be designed to influence user changes in skill-based, cognitive, and affective outcomes (Santhanam et al., 2013). Our study only evaluated the affective outcome (e.g., trainees' gained understanding of the selected IT) and did not include skill-based (e.g., task performance) or cognitive outcomes (e.g., mental models). Thus, we suggest that future research study training outcomes from other perspectives for more insights.

Second, in this study we did not intend to identify multiple technological factors as the influencers of training outcomes. We focused on high and low compatibility between software and hardware and designed an experiment to compare the results. Meanwhile, we believe that studies involving cognitive, technological, or environmental factors are equally important to generating knowledge to the IT training literature. Hence, future research should consider looking at the impact of other technological factors on training outcomes or including different types of factors (cognitive, technological, and environmental) for their direct or indirect effects. Third, the experiment in this study was based on a training simulation with university students. Although students are appropriate for business-oriented experiments (Lee & Dennis, 2012), an experiment with real-world frontline workers can help further reduce interpretation bias. Therefore, we encourage that future studies explore the possibilities of accessing samples in the related industries. Fourth, we did not provide additional background information beside gender, GPA, and major (business vs. engineering) about our student subjects as all of them were freshmen or sophomore enrolled in an introductory course. They shared many similar characteristics. For example, these students shared the same age range, from which we could not see much variation. However, future research may consider sampling other subject types and collecting more background information such as race, age, technological fluency, and career-related variations to reveal more insight.

## Conclusion

With the growing investment in IT for frontline employees, numerous organizations have started to develop IT training programs, hoping to facilitate the adoption and use of related IT in the frontline job. IT training at the front lines is not always related to software as frontline job usually involves both hardware and software. When different generations/iterations of hardware and software are involved, significant compatibility issues may not be salient and thus easily neglected during the training design process. This study focuses on this overlooked but important technological factor – compatibility – in the frontline IT training context. By using a treatment group (high compatibility) and a control group (low compatibility) in a three-phase training experiment, we investigated how hardware-software compatibility impacts the trainees' learning outcome over time. The results revealed that high compatibility promotes trainees' understanding of the target technology while low compatibility impedes trainees from accumulating useful IT knowledge for their job performance over time. This research enriches the literature of IT training by studying the effect of hardware-software compatibility on training outcome of frontline employees using a longitudinal research design. This study also provides valuable insights for organizations that are seeking to design effective IT training programs for frontline employees.

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# Appendices

## *Appendix A. Demonstration of the GIS Tools Included in this Experiment*


(a) (b) (c)

**Figure A1 - Hardware and software required for the cloud computing training experiment**

The necessary tools and devices are shown in Figure A1. The purpose of each tool is stated as follows:

(a) RFID tag – We buried many of these tags to mark critical subterranean and terranean assets, i.e., water lines, gas lines, storm drains, storm-water flow, electric assets, sewer, before the actual training.

(b) Magnetic wand (metal detector) – During phase 2 of the experiment, students were trained to use these wands to locate the pre-buried RFID tags.

(c) RFID tag reader/writer – During phase 2, each RFID tag reader/writer was connected to a smartphone through a mobile app. Students needed to use this device to verify the type of the underground asset that they just found via the magnetic wand.

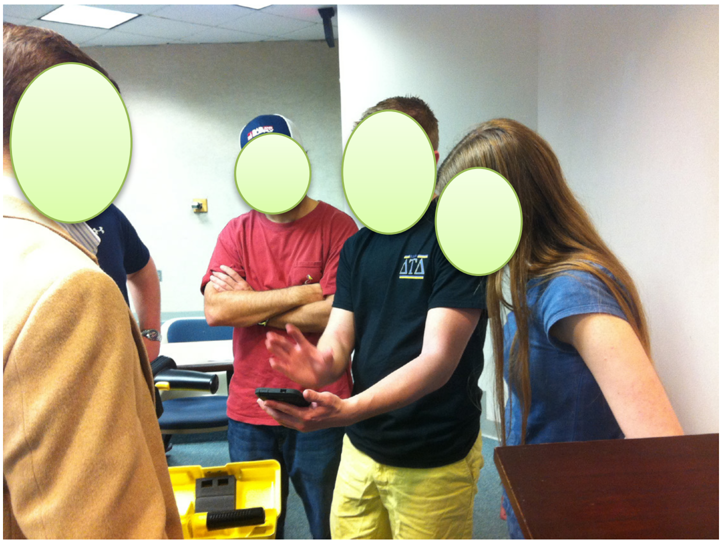

**Figure A2 - Demonstration on the application of the tools involved in the experiment**

As depicted in Figure A2, the magnet- and RFID-based markers needed to be buried about 8 - 12” below ground but directly above the assets (d). Then, during phase 2 of the experiment, both the geospatial data and asset information were written to the cloud server via the mobile app (e). Meanwhile, multi-media information, i.e., pictures relating to the assets could also be stored into the cloud-based GIS (f). After the field work, trainees could view, manipulate, and transfer the asset data in real-time across any compatible mobile devices and computers (g).

## Appendix B. Demonstration of Activities Involved by Phase

We took pictures during each phase of the experiment to help visualize the entire training and hands-on process.

**Phase 1: Student Simulation**



**Phase 2: Field Experiment**

(a) On-campus field (treatment group)

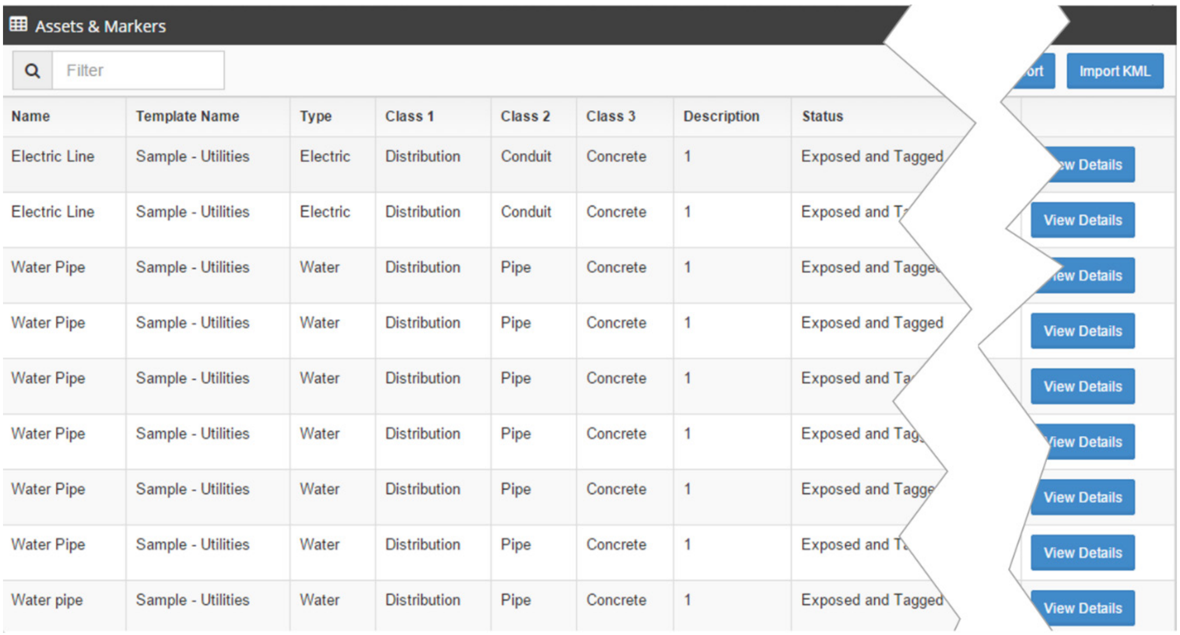
(b) Off-campus field (control group)


DOI: 10.17705/1pais.13301

### Phase 3: Data Analysis

After checking the data stored in Phase 2 and correcting errors, students were required to export the data into an excel (.csv) file and import the data into Google Maps for further visualization. The following figures show an example of the data import results on Google Maps.

(a) Data stored in the online GIS application



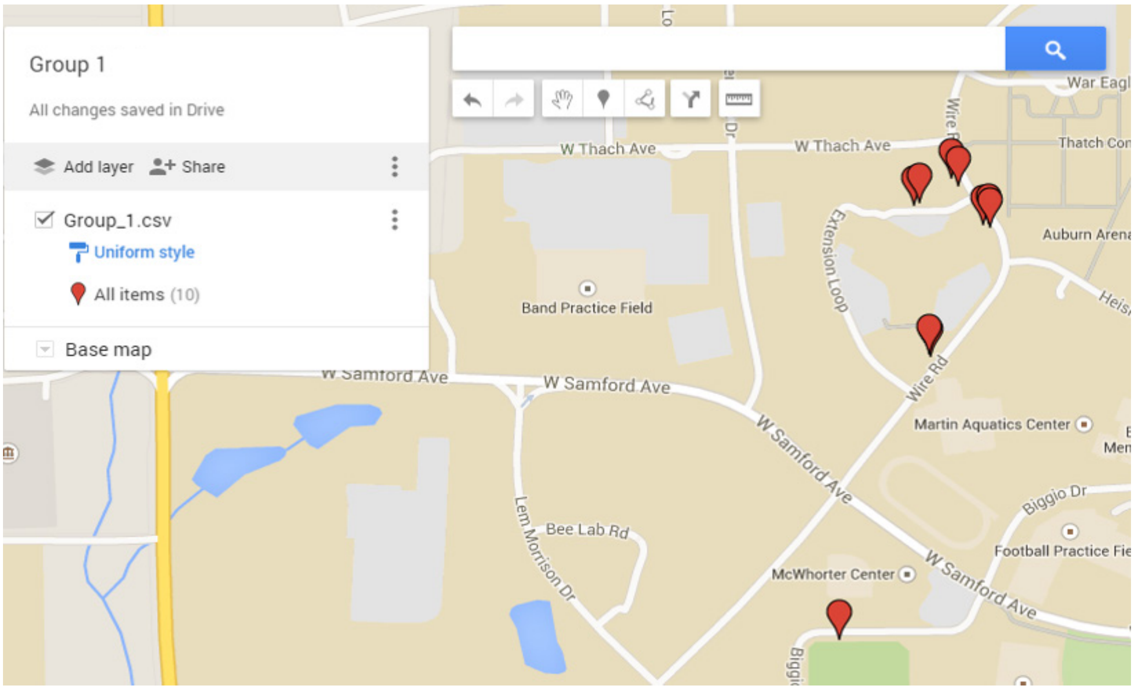
Assets & Markers

Filter

ort Import KML

| Name | Template Name | Type | Class 1 | Class 2 | Class 3 | Description | Status | |
|---|---|---|---|---|---|---|---|---|
| Electric Line | Sample - Utilities | Electric | Distribution | Conduit | Concrete | 1 | Exposed and Tagged | ew Details |
| Electric Line | Sample - Utilities | Electric | Distribution | Conduit | Concrete | 1 | Exposed and T | View Details |
| Water Pipe | Sample - Utilities | Water | Distribution | Pipe | Concrete | 1 | Exposed and Tagge | iew Details |
| Water Pipe | Sample - Utilities | Water | Distribution | Pipe | Concrete | 1 | Exposed and Tagged | View Details |
| Water Pipe | Sample - Utilities | Water | Distribution | Pipe | Concrete | 1 | Exposed and Ta | View Details |
| Water Pipe | Sample - Utilities | Water | Distribution | Pipe | Concrete | 1 | Exposed and Tag | iew Details |
| Water Pipe | Sample - Utilities | Water | Distribution | Pipe | Concrete | 1 | Exposed and Tagge | View Details |
| Water Pipe | Sample - Utilities | Water | Distribution | Pipe | Concrete | 1 | Exposed and T | View Details |
| Water pipe | Sample - Utilities | Water | Distribution | Pipe | Concrete | 1 | Exposed and Tagged | View Details |

(b) Data visualization realized on Google Maps



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