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The Analysis of Association between Learning Styles and a Model of IoT-based Education : Chi-Square Test for Association

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Abstract

The Internet of things (IoT) is a system of interrelated computed devices, digital machines and any physical objects which are provided with unique identifiers and the potential to transmit data to people or machine (M2M) without requiring human interaction. IoT devices can be used to monitor and control the electrical and electronic systems used in different fields like smart home, smart city, smart healthcare and etc. In this study we introduce four imaginary IoT devices as a learning support assistants according to students' dominant learning styles measured by Honey and Mumford Learning Styles: Activists, Reflectors, Theorists and Pragmatists. This research emphasizes the association between students' strong learning styles and a preference to appropriate IoT devices with specific characteristics. Moreover, different levels of IoT devices' architecture are clearly explained in this study where all the artificial devices are designed based on this structure. Data analysis of experiment were measured by the use of chi square test for association and research results showed the statistical significance of the estimated model and the impacts of each category over the model where we finally got accurate estimates for our research variables. This study revealed the importance of considering the students' dominant learning styles before inventing a new IoT device.

Keywords : IoT based Education, Learning Styles, Chi-Square Test for Association

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1. Introduction

Internet of things (IoT) is a network of intelligently connected things with embedded sensors and actuators that is used to gather data and share it with other things [Madakam et al., 2015] introduced first by Kevin Ashton in 1999 [Ashton, 2009]. The IoT network connects different types of devices like personal computers, laptops, tablets, smartphones, PDAs and other hand-held embedded devices [Roy et al., 2017]. Others include devices to measure blood pressure, heart rate, devices like biochip bracelets [Mayer and Baeumner, 2019] for pets or farm animals, devices to call emergency services, robots, autonomous vehicles, home appliances, etc. These devices gather useful information with a variety of sensors and data collection technology, then transmits it to other processing devices for interpretation and decision-making.

In education, mobile-enabled solutions will tailor the learning process to each student's needs, improving overall proficiency levels, while linking virtual and physical classrooms to make learning more convenient and accessible [Association, 2014]. According to this study IoT might serve as backbone for ubiquitous learning environment, and enable smart environments to recognize and identify objects, and retrieve information from the internet to facilitate their adaptive functionality [Xue et al., 2011].

IoT has not only changed the traditional teaching practices but has also brought changes in the infrastructure of educational institutions [Kortuem et al., 2013]. Technology in education has played a significant role in connecting and educating the students. This study analyzes the association between the students' preferences to artificial IoT devices and their dominant learning styles. In our research we have built four imaginary IoT devices, smart voice recorder for group discussions, smart headset for concentration, smart education storage ring and smart organized backpack, which will be measured by Honey and Mumford learning styles [Duff and Duffy, 2002], where there are activists, reflectors, theorists and pragmatists. Observing the diversities of these IoT devices according to their functionalities and descriptions, we analyzed students learning styles by using Chi-Square Test for Association [Agresti, 2006].

The association between our two variables, that are learning styles and preference to IoT devices, constitutes the basis of the research hypotheses.

In the next section we provide the related works about internet of things, the usage of IoT in education, IoT devices' architecture and "Honey and Mumford Learnings Styles", describing each style's specification. Furthermore, in "Data Analysis and Research Methodology" section we explain our research model, its implementation, design of experiment with four different artificial internet of things devices. Finally, "Results and Conclusion" part-presents our research results measured by Chi-Square Test for Association where we represented all our findings with appropriate tables and showed the analysis of all our hypothesis and then concluded our analysis and discussed its limitations.

2. Background

2.1 Internet of Things

The term "Internet of things" is used as a general keyword to cover various aspects related to the expansion of the Internet into the physical sphere through the widespread implementation of spatially distributed devices with embedded identification, sensing and actuation capabilities. IoT foresees a future in which digital and physical objects can be connected using appropriate information and communication technologies to create a whole new class of applications and services. [Borgia, 2014]. Over the past years, internet of things (IoT) has become one of the most important technologies of the 21^{st} century. Now that we can connect everyday objects like home supplies, cars, industry technologies, learning support devices and so on to the internet via embedded devices, seamless communication is possible between people, processes, and things themselves. By means of low-cost computing, the cloud, big data, analytics, and mobile technologies, physical objects or any things are able to share and collect data with minimal human intervention. In this fourth industrial revolution era, digital systems can record, monitor, and adjust each interaction between connected things. The physical world meets the digital world and they cooperate. Therefore, IoT represents a worldwide network of uniquely addressable interconnected objects with an interconnection of sensing and actuating devices providing the ability to share information across platforms through a unified framework, developing a common operating picture for enabling innovative applications. This is achieved by seamless ubiquitous sensing, data analytics and information representation with Cloud computing as the unifying framework. Therefore, the Internet of Things aims to improve one's comfort and efficiency, by enabling cooperation among smart objects.

The 21^{st} century students build confidence in managing their own learning, learn by doing connecting the classroom to the larger world, thrive in positive school cultures where they are engaged and motivated to excel, develop an understanding of global challenges and a commitment to act as responsible citizens. Learning demands new pedagogical and technological approaches to using technology [Mcrae et al., 2018]. It is the responsibility of all educators to prepare students for the demands of an ever-changing world, through facilitating learning in a technology-rich environment, where students and teachers don't just learn about technology, they use it to achieve powerful teaching and learning by improving student learning expectations. Schools today focus on student-centered needs that enable them to employ technological resources to enhance and advance their educational experience [Maenpaa et al., 2017]. The goal of the educational technology program is to promote the ethical and responsible use and strengthen the teacher-student relationship by building higher-order thinking skills, as well as technology literacy skills, to maximize the uses of technology for authentic purposes. Educational Technology shall enhance achievement and will be incorporated in all disciplines. Usage of technology will help teachers implement a universal design for learning which aims to provide equal opportunities to learn. Technology will allow teachers to "present information and content in different ways" (what), "differentiate the ways that students can express what they know" (how), and "stimulate interest and motivation for learning" (why) [Hollier et al., 2017]. This creates an active, engaged learning atmosphere in the classroom.

Apart from student personal perspective of IoT, smart classrooms concept is very important. This concept means an intellectual environment equipped with advanced learning aids based on latest technology or smart things [Gul et al., 2017]. These smart things can be cameras, microphones and many other sensors, which can be used to measure student satisfaction regarding learning or many other related things. The smart object provides ease and comfort for class management. Use of IoT in a classroom may help to provide a better learning and teaching environment. Smart Classroom Management : The term "classroom management" means a way or approach a teacher uses to control his classroom. Smart devices have made it possible for a teacher to decide when he should speak louder when students are losing interest, or their concentration level is decreasing [Rytivaara, 2012]. The use of IoT devices for teaching and learning purposes is a hot trend among institutions across the world which provides a new and innovative approach to education and classroom management. Such tools are already being utilized. Some of the commonly used IoT devices in the classroom are : Interactive Whiteboards, Tablets and Mobile devices, 3-D Printers, eBooks, Student ID Cards, Temperature Sensors, Security Cameras and Video, Room Temperature Sensors, Electric Lighting and Maintenance, Attendance Tracking Systems, Wireless door locks [Gul et al., 2017]. Smart classrooms allow teachers to know what students want to learn and the way they want to learn which is beneficial both for faculty and students. Moreover, smart classrooms help students to understand the real purpose of using technology which also makes the learning process easier [Chang, 2011]. The advancement in the field of technology in education has facilitated educators to design classrooms which are productive, useful, and collaborative and managed through IoT.

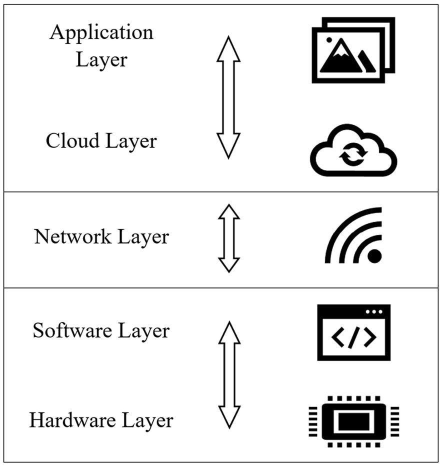
2.2 The Levels of IoT Architecture

Internet of things involves many technologies including architecture, sensors, coding, transmission, data processing, network, application and etc. [Ning and Wang, 2011]. IoT development depends not only on the progress and standardization of technologies, but also on the improvement of our social perception, knowledge, rules and laws. For example, in the future IoT era, the way we live like components or nodes of the network and the exposition of our activities to the public may bring forth many serious security and privacy problems. The standard, reliability, and robustness are also key concerns for IoT development.

The Internet, that we are using today, works with TCP/IP protocol stack for communication between network hosts, which was proposed long time ago [Khan et al., 2012]. On the other hand the IoT connects billions of objects that will create much larger traffic and therefore much more data storage is needed [Tan and Wang, 2010]. Since IoT connects everything and everyone to exchange information among themselves, the traffic and storages in the network will also increase in the exponential way. Thus, IoT development depends on the technology progress and design of various new applications and business models.

In our research we propose three layer of IoT architecture as shown in 〈Figure 1〉 below :

The first layer, which is perception layer, consists of the physical objects and sensor devices. The sensors can be RFID, 2D-barcode, or Infrared sensor depending upon objects identification method. This layer basically deals with the identification and collection of objects specific information by the sensor



<Figure 1> IoT Architecture

devices. Depending on the type of sensors, the information can be about location, temperature, orientation, motion, vibration, acceleration, humidity, chemical changes in the air etc.

The collected information is then passed to the next layer, that is network layer, for its secure transmission to the information processing system. This layer is also known as 'Transmission Layer', which securely transfers the information from sensor devices to the information processing system. The transmission medium can be wired or wireless and technology can be 4G, 5G, Wi-Fi, Bluetooth, infrared, ZigBee and so on depending upon the sensor devices. Consequently, the network layer transfers the information from perception layer to the next layer, that is middleware layer. The devices over the IoT implement different type of services. Each device connects and communicates with only those other devices which implement the same service type. This layer is responsible for the service management and has link to the database. It receives the information from the network layer and store in the database. It performs information processing and ubiquitous computation and takes automatic decision based on the results.

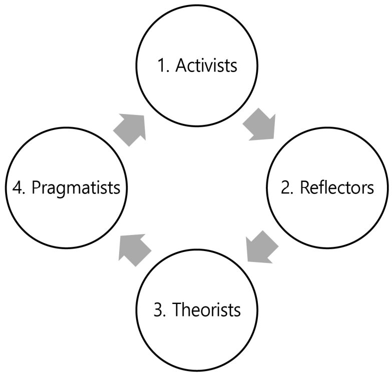
Application layer provides global management of the application based on the objects information processed in the middleware layer. The applications implemented by IoT can be smart health, smart energy, smart home, smart city and so on. And finally business layer is responsible for the management of overall IoT system including the applications and services. It builds business models, graphs, flowcharts and so on, based on the data received from the application layer. The real success of the IoT technology also depends on the good business models. Based on the analysis of results, this layer helps to determine the future actions and business strategies [Khan et al., 2012].

2.3 Learning Styles

Individual learning styles differ, and these individual differences become even more important in the area of education [Säljö, 1981]. Learning style is defined as an individual's inherited foundation, particular past life experience and the demands of the present environment that emphasize some learning abilities over others [Cassidy, 2004]. Educators should be aware of how people obtain and preserve skills and how they access information to help their progress. Some scholars indicate that a primary goal in studying a new medium of communication for educational delivery must be the identification of its impact on learning. Students may benefit from understanding their own learning style by taking measures to adjust the way they acquire knowledge. A definition of "learning styles" is "characteristic cognitive, effective, and psychosocial behaviors that serve as relatively stable indicators of how learners perceive, interact with, and respond to the learning environment. Learning styles are considered by many to be one factor of success in higher education. Confounding research and, in many instances, application of learning style theory has begat the myriad of methods used to categorize learning styles. No single commonly accepted method currently exists, but alternatively several potential scales and classifications are in use. Most of these scales and classifications are more similar than dissimilar and focus on environmental preferences, sensory modalities, personality types, and cognitive styles. Lack of a conceptual framework for both learning style theory and measurement is a common and central criticism in this area. In 2004 the United Kingdom Learning and Skills Research Center commissioned a report intended to systematically examine existing learning style models and instruments. Moreover, many researchers have argued that knowledge of learning styles can be of use to both educators and students. Faculty members with knowledge of learning styles can tailor pedagogy so that it best coincides with learning styles exhibited by the majority of students. Students with knowledge of their own preferences are empowered to use various techniques to enhance learning, which in turn may impact overall educational satisfaction. This ability is particularly critical and useful when an instructor's teaching style does not match a student's learning style. Compounding the issue of learning styles in the classroom has been the movement in many collegiate environments to distance and/or asynchronous education. This shift in educational modality is inconsistent with the learning models with which most older students and adult learners are accustomed from their primary and high school education. Alternatively, environmental influences and more widespread availability of technological advances may make younger generations of students more comfortable with distance learning.

When we learn something new, our first concern is generally what we have learnt-very few people stop to actually consider how they learn. Learners often operate with the same learning methods for years, without any thought as to whether it is the most effective way to absorb and retain information. There is no single "most effective" way of learning; it varies from person-to-person and also depends significantly on the task or the information. Once you know the different approaches to learning, you can consider which is most beneficial for you and when each style is appropriate.

Though there are many different theories and frameworks regarding learning styles, Peter Honey and Alan Mumford [Mumford and Honey, 1986] identified four different approaches people took to learning new information, as it is shown in ⟨Figure 2⟩.



⟨Figure 2⟩ Mumford and Honey Learning Styles

In their view, most people generally stick to one of the styles, or vary between two depending on the scenario. Each of these styles comes with different educational activities which may be more appropriate to those in-

〈Table 1〉 Mumford and Honey Learning Styles Attributes

Learning Style	Attributes
Activists	• Learn by doing, and happy to jump in • Enjoy the challenge of new experiences, without bias • Often guilty of acting before they think • Do not learn well from teaching, theory, reading or analyzing data
Reflectors	• Learn through observation and reflecting on results • Prefer to watch from the sidelines • Take information in from multiple perspectives and work to a conclusion • Reflectors are not good at leading activities or being rushed, with no preparation
Theorists	• Like to understand the theory behind actions • Enjoy models, concepts and facts • Analyze and synthesize testable hypotheses • Not suited to learning without instruction • Not good in situations that involve 'feelings' or when objectives or instructions are ambiguous
Pragmatists	• Need to be able to see how they apply their learning to the real world • Abstract concepts are useless if they cannot see how it is applicable • Enjoy trying new theories and techniques • Do not happily engage when objectives and instructions are unclear, or when it is heavy in theory

dividual learners, listed in 〈Table 1〉 alongside attributes of each style. Understanding each student's learning style is based on the attributes of each, or a questionnaire designed by Honey and Mumford. Anyone can identify his or her specific style and therefore choose activities which are beneficial to their learning.

3. Data Analysis and Research Methodology

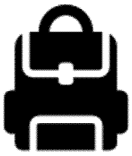
The aim of our research is to analyze the association between the preferences of artificial IoT devices among students and their dominant learning styles. Observing the diversities of these IoT devices according to their functionalities and descriptions, we analyze students' learning styles by using Chi-Square Test for Association and guide them by applying research results for using appropriate internet of things devices according to their learning styles.

3.1 Hypotheses

The association between preferences on imaginary IoT devices, taken as a treatment is shortly presented below, and students' dominant learning styles constitutes the basis of the research hypotheses.

Learning emerges from the interaction of an information and a student's learning style. According to Kolb's experiential learning theory [Kolb, 1985], it works on two levels : a four-stage cycle of learning and four separate learning styles. Honey and Mumford's Learning Style Questionnaire (LSQ) [Duff and Duffy, 2002] has been proposed as an alternative for Kolb's Learning Style Inventory (LSI) and a later refined version [Cornwell and Manfredo, 1994]. The LSQ has been widely applied in the fields of information systems, management training and education [Honey, 1992]. Mumford and Honey Learning Styles Much of learning theories are concerned with the learner's internal cognitive processes. The treatment of our study, which is IoT artificial equipment, is developed according to each learning style's strong points, as shown in 〈Table 1〉. Each device's definition and short description is given below, following our research hypotheses :

Device #1 – Smart Organized Backpack



Definition : This device has certain sensors to help students not to forget or lose their college belongings.

Short Description : Every college or university student has his own backpack where he or she put their books, laptop, tablet, pens, pencils and so on. We know that many students often forget somewhere their belongings or even lose them. In order to prevent this kind of problems to happen, we think that smart organized backpack would be a good solution for that. It works with smart phone where there is a special application of this device. Students have to enter all their belongings according the place it should be in backpack, where there are certain sensors which give signal if any of student's belonging is not in appropriate place. And if something is missing, sensors immediately send warning message to student by application notification.

Students who enjoy carrying out plans and involving themselves in new and challenging and have a tendency to act on gut feelings rather than logical analysis, rely more heavily on people for information than on their own technical analysis. We thus hypothesize :

Hypothesis 1 (H1). *Students with "Activists" dominant learning style will prefer Smart Organized Backpack device.*

Device #2 – Smart Voice Recorder for Group Discussions

Definition : This device helps students when they have different group meetings or discussions.

Short Description : While making any group projects or conversations, this device records all students' voices and recognizes them individually. Stores all discussion in its memory and generates main conclusion. Which means that by machine learning algorithms this device can understand participants' speech separately and then, gathering all necessary information make a logical conclusion. Furthermore, there will be no need to make extra notes for students. After generating main conclusion of the group meeting, smart voice recorder transfers main data to its own smart phone application. This application stores all group discussions separately recording date of the meeting, group name, project title and so on. Smart voice recorder can work with battery up to 10 hours on a single charge.

Students who learn best from activities where they are asked to produce reports that carefully analyze a situation or issue, and also where there is a strong element of passive involvement such as listening to a speaker or watching a video. Thus, we hypothesize:

Hypothesis 2 (H2). *Students with "Reflectors" dominant learning style will prefer Smart Voice Recorder for Group device.*

Device #3 - Smart Headset for Concentration

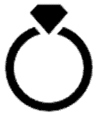
Definition : This device helps students to be more concentrated when they study individually

Short Description : Nowadays there are too many different things which interfere us with studying and do not let us be concentrated on our self-development. Things like socialnetwork sites, different chats or chat groups, news and so on are really being a big obstacle to be a highly focused person. Therefore, we think that the device like smart headset for concentration would be a good solution for this problem. This headset has some sensors which measure people's brain waves which is called electroencephalogram (EEG). And these EEG sensors alert student when he or she is interrupted by someone or something losing his concentration. This device works with smart phone application and every student is able to track all his studying productivity. Moreover, they can track their daily, weekly and monthly concentrated studies and compare with other friends who use smart headset for concentration as well. This device has a battery life up to 5 hours on a single charge.

Students who are best at understanding a wide range of information and putting it into concise, logical form. Moreover, this type of students like working with handouts, something to take away and study. They learn best from activities where the learning forms a part of conceptual whole, such as a model for a theory. We thus hypothesize :

Hypothesis 3 (H3). *Students with "Theorists" dominant learning style will prefer Smart Headset for Concentration device.*

Device #4 - Smart Education Storage Ring



Definition : By wearing this device, students keep all their education related data in its memory card.

Short Description : If in the past students used to carry too many books, files, notebooks and so on, nowadays they have electronic versions of almost every educational material in internet. Therefore, flash cards, memory cards, hard disks appeared to help people to keep some necessary files at these devices. But all of these devices are too broad and general for using only in education purpose. Thus, we think that device like smart education storage ring would be exactly what students need. It connects to smart phone where it has its own application, and by using this application, students can share their necessary data among each other without the need of any computer or laptop. This small ring has a capacity of 1TB memory, works with Bluetooth 5.0 which makes it much easier to connect to bandwidth. In the smart phone application, there is a very convenient interface where the student can divide all educational materials according to his wish, for example sort files according to a course name, major lessons, current semester and previous ones and so on.

Students who like to work independently as a solo, especially on problems like technical tasks and theories where there is a deductive reasoning. They are best at finding practical uses for ideas, theories and as a formal learning style, these learners prefer to experiment with new ideas, simulations, laboratory assignments, and practical applications. Thus, we hypothesize:

Hypothesis 4 (H4). *Students with "Pragmatists" dominant learning style will prefer Smart Education Storage Ring device.*

The hypothesized relationships were tested in an experiment based research with a treatment, which is IoT imaginary devices, and described in the next section.

3.2 Data Setup

The data was collected from Hanyang University students on the basic of experiment which contained two parts of questionnaire. For data collection, college students were chosen as the most appropriate subjects, since they could give more objective opinion about IoT artificial devices rather than elementary, middle or high school students, who would probably face some difficulties in understanding the features of all IoT imaginary devices and rate them accurately. All of the 40 subjects were independent to fill up the experiment and there was no relationship among the observations. Students were arranged to seat quite far from each other in order to complete two different questionnaires relating their preferences to artificial IoT devices and learning styles. Treatments in our experiment were four IoT Imaginary devices (Smart Organized Backpack, Smart Voice Recorder for Group, Smart Headset for Concentration and Smart Education Storage Ring), which they had to first, read all of them, and only then, choose the most preferred device. That was our dependent variable-"Preferences to IoT Imaginary Devices". In the second part of the experiment, students were asked to fill up Mumford and Honey learning styles questions in order to realize their dominant learning styles, which was our independent variable-the "Mumford and Honey learning styles", with four categories as well : activists, reflectors, theorists and pragmatists. Implementing our experiment, we measured the association between our dependent and independent variables. Upon the completion of our experiment, as a motivation, we let the students know their strong and dominant learning styles according to their answers.

3.3 Data Analysis Method

The chi-square test for association determines whether there is an association between two nominal variables [Arnholt, 2007]. It does this by comparing the observed frequencies in the cells to the frequencies we would expect if there was no association between the two nominal variables. As the expected frequencies are predicated on there being no association, the greater the association between the two nominal variables, the greater we would expect the observed frequencies to differ to the expected frequencies. In our research we have two nominal variables : Mumford and Honey Learning Style (e.g., four groups : activists, reflectors, theorists and pragmatists) and IoT Imaginary Devices (e.g., four groups : device 1, device 2, device 3, device 4). The chi-square test for association will find evidence against the null hypothesis. It will do this by calculating a significance value (i.e., p-value). If the p-value is sufficiently small (usually $p < .05$), we can conclude that there is strong enough evidence against the null hypothesis of independence and that there is an association between the two variables in the population.

4. Study Results

Our research analysis was conducted by SPSS Statistics 24 where we analyzed chi-square test for association, moreover we generated the tests for the strength of association, as well as produced adjusted standardized residuals that is used when the chi-square test for association is statistically significant.

Since our research is of two variables that each have four categoriesas we can see from 〈Table 2〉 (i.e., a 4×4 crosstabulation), there are 16 cells in our design that we should evaluate to interpret the data (i.e., 4×4 = 16). The "% within IoT Imaginary Device" row expresses the observed counts in each cell of that row compared to the total in that row as a percentage. For example, out of 12 students who preferred dev1, 8 were activists. That is, 66.7% (i.e., 8÷12×100 = 66.7) of activists who preferred dev1, which is the figure we see in the yellow highlighted cell above. As a proportion this would be **0.667** (i.e., 66.7÷100 = 0.667). In addition, we can think in terms of the column variable and describe the percentage of devices that were preferred by the activists. This result is found in the "% within Learning Style" row and shows that 72.7% of flats sold were sold to single males (i.e., 8÷11×100 = 72.7). As a proportion this would be 0.727 (i.e., 72.7÷100 = 0.727).

We can see in 〈Table 3〉, the chi-square statistic is equal to 30.498. To determine whether the test is statistically significant we need to compare this result to a chi-square distribution with 9 degrees of freedom (i.e., the "df" column). The result is found in the "Asymptotic Significance (2-sided)" column, which shows the p-value for this test. In our pre-test, $p < .0005$. Therefore, we have a statistically significant result (i.e., because $p < .0005$ satisfies $p < .05$). This means that there is an association between our two variables.

〈Table 2〉 IoT Imaginary Device * Learning Style Crosstabulation

			Learning Styles				Total
			activ	refl	theor	pragm	
IoT Imaginary Device	dev1	Count	8	2	1	1	12
		% within IoT Imaginary Device	66.7%	16.7%	8.3%	8.3%	100.0%
		% within Learning Style	72.7%	18.2%	12.5%	10.0%	30.0%
		Adjusted Residual	3.6	-1.0	-1.2	-1.6	
	dev2	Count	1	6	1	1	9
		% within IoT Imaginary Device	11.1%	66.7%	11.1%	11.1%	100.0%
		% within Learning Style	9.1%	54.5%	12.5%	10.0%	22.5%
		Adjusted Residual	-1.3	3.0	-.8	-1.1	
	dev3	Count	1	1	5	2	9
		% within IoT Imaginary Device	11.1%	11.1%	55.6%	22.2%	100.0%
		% within Learning Style	9.1%	9.1%	62.5%	20.0%	22.5%
		Adjusted Residual	-1.3	-1.3	3.0	-.2	
	dev4	Count	1	2	1	6	10
		% within IoT Imaginary Device	10.0%	20.0%	10.0%	60.0%	100.0%
		% within Learning Style	9.1%	18.2%	12.5%	60.0%	25.0%
		Adjusted Residual	-1.4	-.6	-.9	3.0	
Total		Count	11	11	8	10	40
		% within IoT Imaginary Device	27.5%	27.5%	20.0%	25.0%	100.0%
		% within Learning Style	100.0%	100.0%	100.0%	100.0%	100.0%

〈Table 3〉 Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	30.498	9	.000
Likelihood Ratio	26.176	9	.002
Linear-by-Linear Association	12.418	1	.000
N of Valid Cases	40		

A chi-square test for association was conducted between Learning Style and Preference to IoT Devices. There was a statistically significant association between Learning Style and Preference to IoT Devices, $\chi^2(9) = 30.50$, $p < .001$.

4.1 Strength of Association

Cramer's V is a measure that provides an estimate of the strength of the association between our IV and DV and the value of Cramer's V can be found in the Symmetric Measures table, as highlighted below :

We can see in 〈Table 4〉 that the Cramer's V is .504. Cramer's V is a measure of the strength of association of a nominal by nominal relationship. Phi is only suitable when we have two dichotomous variables, so this value is not important for us to report. 〈Table 5〉 shows that Cramer's V ranges in value from 0 to +1 with a value of 0 indicating no association to a value of 1 indicating complete association. Cohen in his early studies [Cohen, 1988] suggested the following guidelines for interpreting Cramer's V :

〈Table 4〉 Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.873	.000
	Cramer's V	.504	.000
N of Valid Cases		40	

〈Table 5〉 Cramer's V Means

Magnitude of effect size	Value of Cramer's V
SMALL	0.1
MEDIUM	0.3
LARGE	0.5

A chi-square test for association was conducted between Learning Style and Preference to IoT Devices. There was a statistically significant association Learning Style and Preference to IoT Devices, $\chi^2(9) = 30.50$, $p < .001$. The association was large [Cohen, 1988], Crame's V = .504.

The chi-square test for association found evidence against the null hypothesis. We also used this to determine whether there is an association between our two variables or, equivalently, whether our two variables are independent. However, even if we found an association, it does not provide us with further details of this association (only that an association exists). Furthermore, we followed up a statistically significant result by the analysis of residuals, which is often described as a cell-by-cell comparison approach [Agresti, 2006; Arnholt, 2007]. A residual is the difference between the expected frequency and the observed frequency. Therefore, we have a residual for each cell of the contingency table. In our research where both nominal variables have four categories, this means that we have 16 residuals ($4 \times 4 = 16$). The larger the residual, the further the observed frequency is from its expected frequency. Analysis of these residuals can be problematic because they tend to be larger in cells with higher expected or observed frequencies [Ebbutt, 2008]. To deal with this problem, the residuals can be standardized so that they have an approximately standard normal distribution with the approximation improving at larger sample sizes [Guitton and Siegel, 1958]. In SPSS Statistics these residuals are called, adjusted standardized residuals. By analyzing these adjusted standardized residuals, we made a cell-by-cell comparison of the expected versus observed frequencies to help understand the nature of the evidence against the null hypothesis [Agresti, 2006]. If an adjusted standardized residual is positive, it indicates that there are more observed frequencies than expected frequencies given the null hypothesis for association. If an adjusted standardized residual is negative, it indicates that there are less observed frequencies than expected frequencies given the null hypothesis for association. Simply put, the larger the absolute value of the adjusted standardized residual, the greater its considered contribution to the chi-square value, and the more that cell provides evidence against the null hypothesis. Stated another way, cells with a large absolute adjusted standardized residual indicate where the lack of association is occurring within the crosstabulation [Kateri, 2014].

Having selected the Adjusted standardized option in SPSS, the adjusted standardized residuals are presented in ⟨Table 6⟩ for each cell of the crosstabulation in the IoT Imaginary Device * Learning Style Crosstabulation table along the "Adjusted Residual" rows, as shown above. As we can see from the table above, the largest adjusted standardized residuals were for dev1, which were preferred by activists, with an adjusted standardized residual of 3.6. There are two recommendations to determine when a cell deviates significantly from independence are when the absolute adjusted standardized residuals are greater than either 2 or 3 [Agresti, 2006]. These recommendations are further clarified as adjusted standardized residuals greater than 2 in absolute value for small tables and greater than 3 for larger tables, in our case we have a small table relatively. Therefore, in our research we have 4 cells with adjusted standardized resi-

⟨Table 6⟩ IoT Imaginary Device * Learning Style Crosstabulation

			Learning style				Total
			activ	refl	theor	pragm	
IoT Imaginary Device	dev1	Count	8	2	1	1	12
		% within IoT Imaginary Device	66.7%	16.7%	8.3%	8.3%	100.0%
		% within Learning Style	72.7%	18.2%	12.5%	10.0%	30.0%
		Adjusted Residual	3.6	-1.0	-1.2	-1.6	
	dev2	Count	1	6	1	1	9
		% within IoT Imaginary Device	11.1%	66.7%	11.1%	11.1%	100.0%
		% within Learning Style	9.1%	54.5%	12.5%	10.0%	22.5%
		Adjusted Residual	-1.3	3.0	-.8	-1.1	
	dev3	Count	1	1	5	2	9
		% within IoT Imaginary Device	11.1%	11.1%	55.6%	22.2%	100.0%
		% within Learning Style	9.1%	9.1%	62.5%	20.0%	22.5%
		Adjusted Residual	-1.3	-1.3	3.0	-.2	
	dev4	Count	1	2	1	6	10
		% within IoT Imaginary Device	10.0%	20.0%	10.0%	60.0%	100.0%
		% within Learning Style	9.1%	18.2%	12.5%	60.0%	25.0%
		Adjusted Residual	-1.4	-.6	-.9	3.0	
Total		Count	11	11	8	10	40
		% within IoT Imaginary Device	27.5%	27.5%	20.0%	25.0%	100.0%
		% within Learning Style	100.0%	100.0%	100.0%	100.0%	100.0%

〈Table 7〉 Adjusted Standardized Residuals

	Learning Style			
IoT Imaginary Device	Activisits	Reflerctors	Theorists	Pragmatists
Device 1	8 (3.6)	2 (-1.0)	1 (-1.2)	1 (-1.6)
Device 2	1 (-1.3)	6 (3.0)	1 (-.8)	1 (-1.1)
Device 3	1 (-1.3)	1 (-1.3)	5 (3.0)	2 (-.2)
Device 4	1 (-1.4)	2 (-.6)	1 (-.9)	6 (3.0)

duals larger than 2, as you can see them in a table format, as shown in 〈Table 7〉 below :

In our research in found that a chi-square test of independence was statistically significant, $\chi^2(9) = 30.50$, $p < .001$, and the association was pretty large Cramer's V = .504. Moreover, as show in 〈Table 7〉 we found that device 1 is more preferred by activists (3.6), reflectors chose device 2 (3.0) rather than other devices, whereas device 3 is more liked by theorists (3.0) and pragmatists are more partial to device 4 (3.0)according to the adjusted standardized residuals that explain our cells deviated from independence, as shown in the table above.

5. Summary, Conclusions, Limitations and Future Implications

This study analyzes the relationship between students' individual preferences for educational conditions under the fourth industrial revolution environments and their individual learning styles. Based on the proper experimental design, it is thought to be a fairly timely topic in situations where changes in educational field by learning support equipment are required, such as covid 19 and etc.

The null hypothesis arising from this research question stated that there was no relationship between students' learning styles and IoT devices' preferences. Due to a lack of research that investigated our research question directly, the theoretical framework for this study was based on an overview of the current research on students'learning styles and also on current research on the preferences of IoT devices which were built artificially according to IoT architecture.

The study utilized a sample of 40 students from Hanyang University, the experiment questionnaire was performed by two parts developed by the researcher. In the first part four artificial IoT devices were presented as a treatment followed with the questionnaire measuring respondents' level of preferences to each device. Furthermore, students were asked to sort all four imaginary IoT devices from most preferred to least preferred ones. In the second part we used Honey and Mumford Leanings Styles questionnaire to collect data on students'dominant learning styles. There was no time limit for completing the questionnaire, therefore the respondents could go back and read any IoT device description if they needed so.

Due to the nature of the data that were collected in this study, Chi Square test for Association was used to analyze the data for relationships. Various other tests such as adjusted standardized residuals, Cramer's

V, the goodness-of-fit test were carried out to check the strength of association between the independent variable, learning style, and the dependent variable, preferences to IoT devices. The significance level of .05 was declared for hypothesis testing.

The results of chi-square test for association showed evidence against the null hypothesis that there was no relationship between students' dominant learning styles and preferences to IoT devices, was found to be false and thus rejected. Researcher determined that there was an association between two variables. A chi-square test of independence was conducted between learning style and preference to IoT devices. There was a statistically significant association between students' learning style and their preference to IoT devices, $\chi^2(9) = 156.313$, $p < .001$. Moreover, Cramer's Vwas measured provide an estimate of the strength of the association between independent and dependent variables, where the value of Cramer's V found a large association [Cohen, 1988], Cramer's V = .589. Furthermore, a statistically significant result by the analysis of residuals, which is often described as a cell-by-cell comparison approach was presented. In this research where both independent and dependent variables were nominal, with four categories each, total 16 residuals were measured. The largest adjusted standardized residuals were for imaginary IoT device #1, which were preferred by activists, with an adjusted standardized residual of 3.6. The research showed 4 cells with adjusted standardized residuals larger than five. The device #1 was more preferred by activists with adjusted standardized residuals 3.6, reflectors chose device #2 with adjusted standardized residuals 3.0 rather than other devices, whereas device #3 was more liked by theorists with adjusted standardized residuals 3.0 and last but not least, pragmatists were more partial to device #4 with adjusted standardized residuals 3.0.

Observing the diversities of IoT devices according to their functionalities and architecture with students' learning styles, this research presented the importance of relationship between preferences to IoT devices and students' learning styles by using Chi-Square Test for Association. Thus, this research measured hypothesis whether each learning style matched the appropriate IoT devices and presented :

1. A statistically significant relationship between "*Activists*" dominant learning style students and their preferences to Smart Organized Backpack device.
2. A statistically significant relationship between "Reflectors" dominant learning style students and their preferences to Smart Voice Recorder for Group device.
3. A statistically significant relationship between "Theorists" dominant learning style students and their preferences to Smart Headset for Concentration device.
4. A statistically significant relationship between "Pragmatists" dominant learning style students and their preferences to Smart Education Storage Ring device.

Nevertheless, the findings of this study have to be seen in light of some limitations. First, we used a small population only analyzing 40 students, which could tend to produce less accurate estimates. Second, the treatment in our research is based on imaginary IoT devices. Even though, we provided a clear explanation and functionality of all four IoT devices, students could face some difficulties in making a preference for the best preferred device because of the lack of practical implementation of those artificial devices.

Despite the limitations, the current study has several implications for further research. Additional variable such as student's gender could be added to verify that it has a significant role in preferences to IoT devices. Moreover, replication studies could be followed to prove the accuracy of the findings of this study with different populations, e.g. students from science and technology departments could be compared with students from business and humanities department. And additional study could be conducted with school administrative perspective IoT devices.

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