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Impact of Students' Backgrounds on Online Learning Behavior: Generation Z Technology Acceptance of E-Learning Technology during COVID-19

Dr. Sanaz Motamedi, University of Florida

Sanaz Motamedi is faculty member at Industrial and System Engineering, the University of Florida after her postdoctoral fellowship at the California Partners for Advanced Transportation Technology program, University of California, Berkeley. Her research

Viktoria Medvedeva Marcus, University of Florida

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Abstract.
The COVID-19 pandemic necessitated a swift transition from in-person to online learning, eliciting a spectrum of responses from students and prompting numerous institutions to develop online programs. Our study explores the challenges Generation Z students faced during the COVID-19 pandemic, with a specific focus on understanding how their backgrounds influenced their interactions with e-learning platforms, including their learning styles, personalities, GPA, housing, voluntariness of use, and quality of internet access. To acquire comprehensive data, we formulated an online survey targeting Generation Z university students with multiple semesters of online learning experience from multiple disciplines including engineering, business, journalism, law, fine arts, education, biology, and more. This survey aimed to collect information on their demographic details, personality traits, learning styles, and perceptions of their online learning experience using the Technology Acceptance Model (TAM) which has been used repetitively in literature. With 1000 valid responses, the survey yielded a substantial dataset for in-depth analysis. After cleaning and transforming the data, we had 948 data points with which to conduct a series of ANOVA analyses; it was found that learning style, personality, and quality of internet access had significant relationships with every TAM factor, including actual use, behavioral intention to use, perceived usefulness, and perceived ease of use. GPA and voluntariness had significant relationships with actual use and perceived usefulness. Housing had no effect on any of the TAM factors. This study provides valuable insights into how students' unique backgrounds shape their educational journeys, insights which program managers and new educators can utilize to inform the design of new programs.

Introduction.

In early March 2020, the World Health Organization declared an outbreak of a novel coronavirus a global pandemic [1]. As COVID-19 guidelines were rapidly put in place, requiring social distancing and closure of many public places, including most schools and universities, who had to quickly pivot to distance learning [2-4]. Schooling did not stop despite the pandemic, but instead began utilizing distance learning, also called online learning or e-learning, which had been growing in popularity in the years leading up to the pandemic, given the added convenience online courses provide to students [4-9]. However, this rapid shift from in-person to online learning was met with varying levels of acceptance and resistance by students, who were suddenly required to use e-learning technology [10-11].

One of the reasons students had a varied response to the rapid shift to online learning was due to individual differences in how students interact with online learning versus traditional, in-person school. These differences are caused, in part, by each student's unique backgrounds: especially their age, gender, personality, and learning style, which lend students to experience and interact with e-learning differently [6-7, 9]. Demographic information such as age and gender have been shown to have an impact on students' perception and use of e-learning technology [7]. Personality and learning style are also characteristics individual to each student that can change how they interact with an online learning environment [6-7, 12-13]. And because e-learning is more self-directed and requires different skills than in-person learning, the effect of students' backgrounds may be different in online settings compared to traditional classroom settings [4, 8-9, 14].

In addition to these differences in students' interaction with online versus in-person school, during the COVID-19 pandemic, students faced many other challenges that impacted their schooling. During the pandemic, students' use of online learning technology was involuntary. Most students using e-learning prior to the pandemic were making a choice to do so, but students taking online classes during the pandemic were doing so because it was the only option available to them. This meant that more students than ever were using e-learning technology, including those who preferred in-person school, those who preferred online school, those who had no experience with online classes, those who had lots of experience with online classes, first year students, last year students, introverted students, extraverted students, and all those in between. We define voluntariness, in the context of this study, to mean whether or not students were taking online classes by choice or were required to because of the impact of the COVID-19 pandemic. Adding to this, many students also experienced changes in their regular living conditions, with some able to move back home to live with their family, some living off campus, some allowed to stay in on campus housing, but others unable to stay in dorms as schools shut down housing. Many students found themselves living in more isolated conditions, different states, and different time zones in the span of weeks [3, 8, 15-16]. These changes also impacted students' access to the internet, which is required for e-learning use. Interpersonal interactions were limited, or did not exist at all, and students no longer were able to attend in person lectures, office hours, or extracurricular events. The chaos caused by the sudden onset and drastic changes due to the pandemic caused many students additional uncertainty, stress, and anxiety, leading to a global increase in mental health challenges faced by university students [3, 16].

While the effects of students' demographics, such as gender and age, have been more closely studied in the past, a gap exists in describing the impact of Generation Z students' learning styles, personalities, GPA, housing, voluntariness, and quality of internet access on their use of online learning technology, especially in the context of the highly disruptive COVID-19 pandemic. Generation Z students, those born between 1997-2012, made up a majority of the populations in high school and college during the pandemic. Generation Z students grew up during a time of immense technological expansion, including technological advancements in education. This study seeks to develop an understanding of how Generation Z students' unique backgrounds influence their use of online learning technologies by analyzing survey responses from 948 Generation Z university students who took online classes during the COVID-19 pandemic.

Literature Review.

Previous studies have sought to understand the relationship between students' demographics, personalities, learning styles, and other factors that influence their acceptance, use, and/or attitude towards using online learning technology. Many studies that focus on learning style, personality, and other demographic factors were conducted prior to the COVID-19 pandemic; while they can help develop an understanding of the impact of these traits during regular use of e-learning, a gap remains in understanding if and how individual students' differences combined with the impact of COVID-19 affected their use of using e-learning technology. Some studies conducted during the pandemic did evaluate the impact of demographics on acceptance and use of e-learning technology, but often had varying results.

Many studies seeking to understand what influences students' use of online learning technology developed models including other factors to explore, and while they collected demographic data, often did not analyze its relationship to behavioral intention to use. Few studies include personality, learning style, demographics, and the impact of COVID-19 all together, but related studies can be synthesized to provide the theoretical foundations for this paper.

Technology Acceptance Model

To start, this study uses the Technology Acceptance Model, or TAM, as a base for understanding students' behavioral intention to use e-learning systems. TAM was developed by Davis, 1989 [17] to predict user acceptance of information technology. The model consists of the factors perceived ease of use, perceived usefulness, behavioral intention to use, and actual use [17]. The TAM model describes the relationship between these factors, where perceived ease of use and perceived usefulness are predictors of behavioral intention to use, and behavioral intention to use predicts actual use [17].

In the TAM model, perceived usefulness is defined as the degree to which an individual believes that using a system would enhance their performance, perceived ease of use is defined as the degree to which a person believes that using a system would be free of physical or mental effort, behavioral intention to use is defined as the cognitive processes, plans, and motivations an individual has to perform a behavior, and actual use is defined as the specific use of a technology, including how frequency of use, time spent using it, and more [17].

Many studies have used the TAM model when analyzing online learning behaviors and have also extended the model with external factors and moderating variables [4, 9, 13-14, 17-18]. This study specifically focuses on understanding the impact of students' backgrounds on their use of e-learning technology, measured through the factors in the TAM model.

Impact of COVID-19 on Use of E-Learning

Several papers have begun to describe the effect of the COVID-19 pandemic on students' use of e-learning technology. In Alavudeen et al., 2021 [8], the influence of COVID-19 related psychological and demographic variables on the effectiveness of e-learning among health care students was investigated. The authors emphasized that the multifactor impact of the pandemic on university students, including the sudden switch to online learning from in-person learning, changes in home lives, impacts to social and psychological wellbeing, and e-learning requiring more self-direction from students, has created a unique learning environment for students that requires understanding their attitudes and perspectives towards online learning to make it more effective [8]. Over half of respondents had no prior experience with e-learning, many reported that they faced poor network connectivity, unawareness of or inexperience with e-learning technology, and increased distractions, factors which impacted their learning experiences. Results revealed that while gender did not impact students' perception of e-learning, living status, negative household history of medical quarantine, and prior experience with e-learning did impact their experience with and perception of e-learning [8].

In Baber, 2021 [9], students' acceptance of e-learning during the COVID-19 pandemic was studied. The paper's framework was an extended TAM model, including the factors of instructor characteristics, student characteristics, and the moderating factor "perceived severity of COVID-19" [9]. Using PLS-SEM to analyze the data, the authors found that perceived ease of use; perceived usefulness; student characteristics such as mindset, motivation, and collaboration; instructor characteristics, such as attitude, competency, and interaction; and perceived severity of

COVID-19 had an influence on students' intention to use e-learning technology [9]. The main limitation this study faced was its small sample size, meaning the results may not be generalizable, and the study did not include demographic data in the analysis [9].

In Mailizar et al., 2021 [4], the authors sought to understand factors that impact university students' behavioral intention to use e-learning during the COVID-19 pandemic by extending the TAM model with the factors of system quality, e-learning experience, and attitude towards use. Attitude, according to this paper, is "a tendency in response to an event in a favorable or an unfavorable way" [4]. Using SEM, they found that attitude towards e-learning use was the most impact factor that influenced students' behavioral intention to use e-learning during the pandemic; the study found that prior e-learning experience did not impact behavioral intention to use e-learning, contrary to other studies [4]. Though this paper does not focus on demographics, personality, or learning style, it does show the importance of attitude to students' intention to use e-learning during the COVID-19 pandemic; attitude is not unrelated to students' other individual characteristics [4].

Impact of Voluntariness on Use of E-Learning

While few have looked into the role of voluntariness of use during the pandemic, some studies conducted prior to the pandemic have included voluntariness in their models. Ramayah, 2010 [18] examined the role of voluntariness in students' use of e-learning. The study used the TAM model, extended with voluntariness as a moderating factor [18]. A survey based on this model received 67 responses, and using factor analysis, the author found that perceived voluntariness did moderate the relationship between perceived ease of use and behavioral intention to use, as well as between perceived usefulness and behavioral intention to use [18]. While this study had a small sample size from only Malaysia and does not focus on the COVID-19 pandemic, it does show that voluntariness has an impact on students' intention to use e-learning technology [18].

Agarwal and Prasad, 1997 [19] also sought to understand the effect of perceived voluntariness in the acceptance of new information technology. Using regression analysis, this study found that perceived voluntariness was significant in explaining current system usage, but not future system use or overall user acceptance [19]. This indicated that voluntariness was important for the initial acceptance behavior, but not for continued use [19]. While this study does not focus specifically on e-learning use in higher education, it does identify a general relationship between system use and voluntariness; understanding the relationship between actual use and voluntariness is important for developing a model describing the involuntary use of e-learning that students faced during the COVID-19 pandemic.

Impact of Learning Style and Personality on E-Learning Use

Several studies have also sought to develop an understanding of the effects of learning style and personality on online learning system use and outcomes. In Baherimoghadam et al., 2021 [20], authors examined the effect of learning style and self-efficacy on satisfaction of e-learning in Generation Z dental students. The study defined learning style as "a combination of cognitive, emotional, and physiological characteristics [which] might indicate how a student can learn," and used the Solomon and Felder learning styles index to measure different learning styles which has four characteristics, including processing, perception, input, and understanding. Using SPSS to analyze their results, the authors found that active processing and global understanding learning style characteristics had significant relationships with e-learning satisfaction [20]. While this study did have a small sample size, and measured e-learning satisfaction versus actual use, the study showed that students' individual learning styles can impact their perceptions of e-learning [20].

To understand if learning styles impact students' performance in online courses, El-Sabagh, 2021 [21] developed an adaptive e-learning environment to measure its impact on student engagement. According to the study, an adaptive e-learning environment "personalizes instruction to reinforce learning outcomes" by dynamically changing the way information is taught "based on the response of the students' learning styles or preferences," rather than that "one style fits all" approach used by non-adaptive e-learning systems [21]. To assess students' learning styles, this study used the Visual, Aural, Read/Write, or Kinesthetic (VARK) learning styles inventory which is a questionnaire consists of 16 items used to assess the respondent's learning style [21]. The study also used the Dixion scale to measure students' engagement using the adaptive or non-adaptive e-learning system; this scale includes the factors of skills, participation/interaction, performance, and emotion [21]. This study found that students who learned through the adaptive system learned more, reflected by their engagement scale responses and overall course outcomes. While this study does not model the relationship between students' learning styles and intentions to use, has a small sample size, and did not occur during the COVID-19 pandemic, the paper showed the impact of learning styles on student engagement and outcomes, with the adaptive e-learning system allowing students to better engage with the material [21].

In Al-Azawei et al., 2016 [14], the effect of students' learning styles in a blended e-learning system (BELS) are examined to understand how individual differences and perceptions impact learner satisfaction and technology adoption. The study defines BELS as "the thoughtful integration of classroom face-to-face learning experiences with online learning experiences," or a classroom setting that utilizes both online learning technology and in-person teaching [14]. The authors used a model based on TAM to investigate the factors impacting technology adoption and extended that base TAM model with the four learning style characteristics, blended e-learning system self-efficacy, and perceived satisfaction. Using PLS-SEM analysis, the study found that, overall, the four learning style factors did not influence user acceptance or satisfaction, and neither did age. This study described a classroom that utilized both in-person and online learning, which students in university during the COVID-19 pandemic did not experience, but their model described one method of including learning styles in a behavioral model for students using e-learning technology.

Kamal and Radhakrishnan, 2019 [12] sought to understand how personality traits and learning styles interact for students using e-learning technology. The study used the Felder-Silverman Index of Learning Styles to assess students' learning styles and used the MBTI inventory to assess personality traits [12]. The authors found that there was significant positive correlation between Extrovert personality and Active processing, Introvert personality and Reflective processing, Sensing personality and intuitive perception, Thinking personality and verbal input, Feeling personality and visual input, Judging personality and sequential understanding, and Perceiving personality and global understanding [12]. These results indicate that personality and learning style are connected, with a preference in one's personality type predicting their preference in learning style when using e-learning technology [12]. While this study does not look into how learning style and personality specifically impact the use of e-learning technology, it does show a relationship between the personality and learning styles of the user [12].

In Keller and Karau, 2013 [6], the authors examined the impact of personality on students' perceptions of the online learning experience. This study defined personality using the Big Five dimensions, which describe personality through the traits of conscientiousness, openness, agreeableness, extraversion, and emotional stability [6]. Using correlation and regression analysis, the study showed that personality and some demographic variables had an effect on students' perceptions of online courses; conscientiousness showed significant positive relationships with all five of the online course impression factors, while agreeableness and openness had positive relationships with value to career [6]. Of the demographic variables, work experience was significant for all online course impression factors except for online course preference [6].

In Rivers, 2021 [13], the author examined the role of personality traits and online academic self-efficacy in acceptance, actual use, and achievement in online learning [13]. The study defined personality as "dimensions of individual differences in tendencies to show consistent patterns of thoughts, feelings, and actions," and to measure specific personality traits, the study used the five-factor model of personality [13]. A survey was created including the Ten-Item Personality Inventory to measure the five-factor model's personality traits, self-efficacy items, TAM model items, and demographics [13]. Using SPSS, the data was analyzed and revealed that agreeableness and conscientiousness had the most positive effect on perceived ease of use, perceived usefulness, attitudes toward use, and online course achievement outcomes [13]. While this study does not include the effect of the COVID-19 pandemic, it shows that personality traits impact e-learning outcomes [13].

Yu, 2021 [7] sought to understand the effects of gender, educational level, and personality on online learning outcomes during the COVID-19 pandemic. The study used the five-factor model [7]. Using linear regression to analyze the data, it was found that education level and personality influenced online learning outcomes [7]. Specifically, extraversion was negatively correlated with online learning outcomes, while conscientiousness, agreeableness, and openness were positively correlated with online learning outcomes [7]. Gender did not have an influence on online learning outcomes [7]. This study was limited by its respondents being only language students in China, and it did not exclusively study Generation Z students, but the results show that personality does have an impact on e-learning outcomes, especially during the COVID-19 pandemic [7].

While these studies begin to describe the impact of demographics, COVID-19, personality, and learning style on students' acceptance, use of, and/or attitude towards e-learning technology [4, 6-9, 13, 18, 20], none directly answer the question of the impact of Generation Z students' learning style, personality, GPA, housing, voluntariness of use, and quality of internet access on their actual use, intention to use, perceived usefulness, and perceived ease of use of e-learning technology during the COVID-19 pandemic. This study will evaluate 948 survey responses from Generation Z university students to begin to understand the answer to this question.

Methodology.

To collect data, an online survey was developed using the Qualtrics software, including background information factors and the TAM model factors. In the background information section, questions included asking about students' age, GPA range, if they had taken online courses before, if they were taking online classes voluntarily online, where they lived while taking online classes, the quality of their internet access while taking online courses, if their learning style was compatible with the e-learning system, and if their personality naturally allowed them to work with the e-learning system. The survey also included four items for each TAM factor, including actual use, behavioral intention to use, perceived usefulness, and perceived ease of use. The model is shown in Fig. 1, and the items used in the survey are shown in Table 1. The study was approved by the International Review Board (IRB).

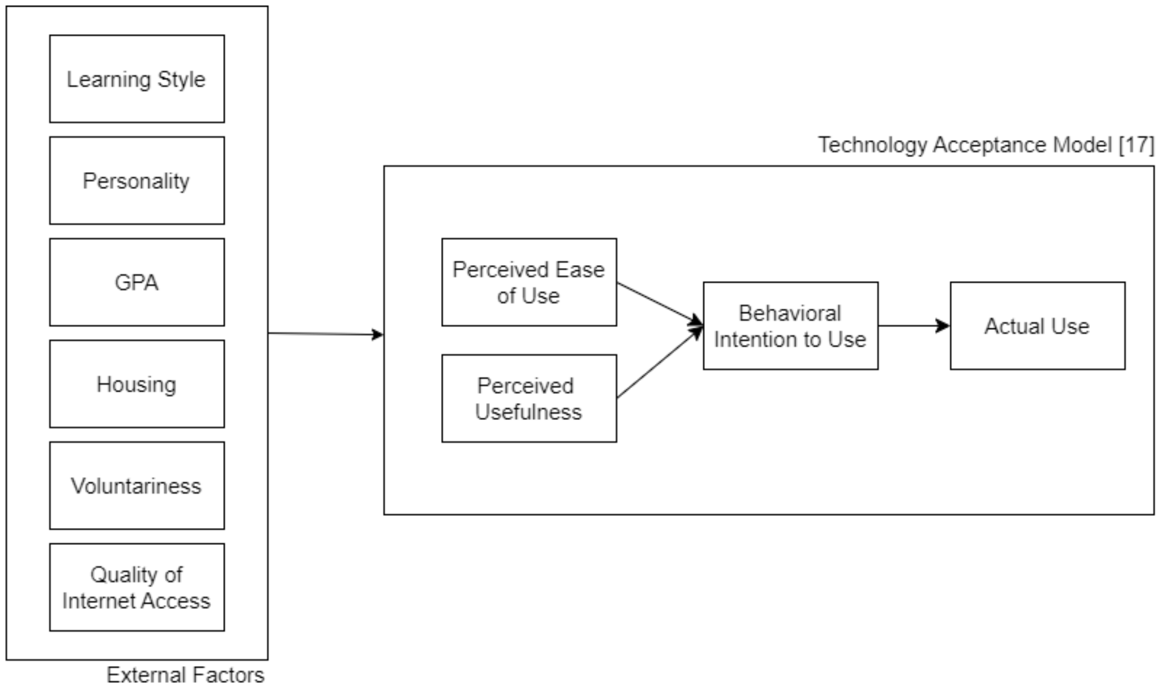

Figure 1. Extended TAM model.

Table 1. Items used in survey.

Item	Wording	Reference
Background		
Age	What year were you born?	
GPA	In what range is your GPA?	
Experience	Have you taken at least three online classes?	
Voluntariness	Were you required to take these classes online?	
Housing	Where did you live while taking online classes?	
Quality of Internet Access	How would you rate the quality of your access to the internet, including Wi-Fi connection, loading speed, physical connection, etc., when using online learning technology?	

Learning Style	My learning style is compatible with the e-learning system.	Modified from [22]
Personality	My personality naturally allows me to work well with the e-learning system.	self-developed
Technology Acceptance Model Factors		
Actual Use 1	I use the e-learning system on a daily basis	[23-25]
Actual Use 2	I use the e-learning system frequently	[19, 23-24]
Actual Use 3	Overall, I use the e-learning system to a great extent	[2, 23, 25]
Actual Use 4	I spend a lot of time using the e-learning system	self-developed
Behavioral Intention to Use 1	I intend to use the e-learning system in the near future	[9, 23, 25-28]
Behavioral Intention to Use 2	I will use the e-learning system on a regular basis in the future	[9, 19, 24-25, 27-28]
Behavioral Intention to Use 3	I intend to use the functions and content of the e-learning system in the future	[9, 23, 25, 27-30]
Behavioral Intention to Use 4	I intend to use the e-learning system as often as needed	[9, 27]
Perceived Usefulness 1	I find autonomy over where and when to use the e-learning system to be useful in my learning	[11]
Perceived Usefulness 2	The features of the e-learning system enhance my learning performance	[4, 9, 14, 17, 23-25, 27-29, 31]
Perceived Usefulness 3	My productivity is elevated through the utilization of e-learning in my study	[4, 9, 13, 17, 23, 27-29]
Perceived Usefulness 4	The features of the e-learning system enhance my learning effectiveness	[9, 13-14, 17, 19, 24-25, 27-29, 31-32]

Perceived Ease of Use 1	I find it easy to use the e-learning system	[9, 13-14, 17, 19, 23-25, 27-29, 32-33]
Perceived Ease of Use 2	I find interacting with the e-learning system to be clear and understandable	[9, 13-14, 17, 19, 23-25, 27, 29, 33]
Perceived Ease of Use 3	Interacting with the e-learning system does not require a lot of mental effort	[14, 25, 27, 33]
Perceived Ease of Use 4	I find it easy to get the e-learning system to do what I want it to do	[9, 13, 17, 19, 23-24, 27-29, 33]

In total, the survey received 1000 responses. Respondents were recruited through professional organization forums, email, group chats, and social media. The data was then filtered to include only those responses that were complete and in the correct age range for Generation Z (1997-2012). The survey also included one duplicated item (Perceived Ease of Use 2 was presented twice) to serve as a verification tool–if this item had matching answers, the response would be included, but if the answers differed, the response was removed. After cleaning the data, there were a total of 948 valid responses.

After filtering and cleaning the data cleaning, some of the data was transformed for proper analysis. For keeping balance within independent variables (e.g. learning style, personality, GPA, housing, and quality of internet access) we combined some of the levels. For example, GPA originally included 5 levels, which were combined to three balanced levels. After the data was collected, cleaned, and transformed, ANOVA analysis was performed.

Results.

Descriptive Analysis.

The survey received a total of 948 valid responses. Among these, 41.5% were female, 57.13% were male, and 1.37% were other. All respondents were in the age range of Generation Z. 95.24% of students had taken at least three online classes, and 47.62% were taking classes online voluntarily. The GPA ranges of respondents are shown in Figure 1. 80.95% of students reported having ‘Good’ to ‘Excellent’ quality of internet access, shown in Figure 2. 38.1% of respondents were living in shared housing, 28.57% were living alone, 28.57% were living with parents, and 4.76% had other housing arrangements, shown in Figure 3.

In this sample, students from many different universities studying many different majors responded. Over 150 unique universities were mentioned, and the top five universities that had the most respondents, in decreasing order, included the University of Florida (12.45%), Princeton University (4.64%), Harvard University (4.43%), Columbia University (4.11%), and Standford University (3.9%), though many more schools were listed. This represents a wide range of American public and private universities, including Ivy League schools, research universities, and state colleges with a broad geographic range. There were also a few international universities, such as Oxford and Cambridge mentioned.

Respondents' majors ranged over the fields of STEM, social sciences, humanities, medicine, and law, with the most mentioned majors including economics, computer science, medicine, business, law, various engineering disciplines, biology finance, psychology, and mathematics. There were also some mentions of fine arts majors, including graphic design, visual and performing arts, music, and more. The largest fields, in decreasing order, were STEM (46.48%), business (12.32%), medicine/heath science (10.56%), humanities (9.51%), social sciences (8.8%), arts (3.52%), law (2.11%), and other (6.7%). This represents a broad range of majors, highlighting the diversity of the sample.

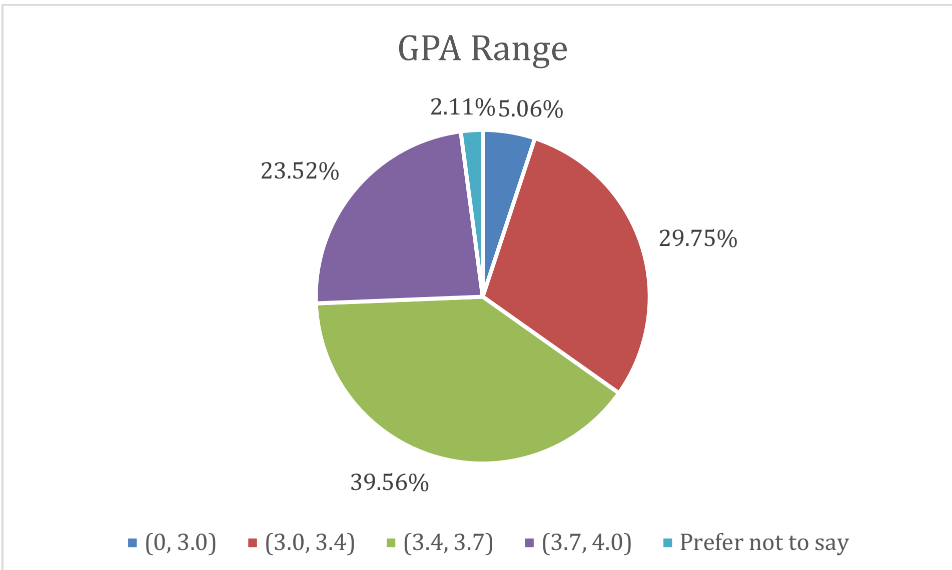

Figure 1. GPA ranges of respondents

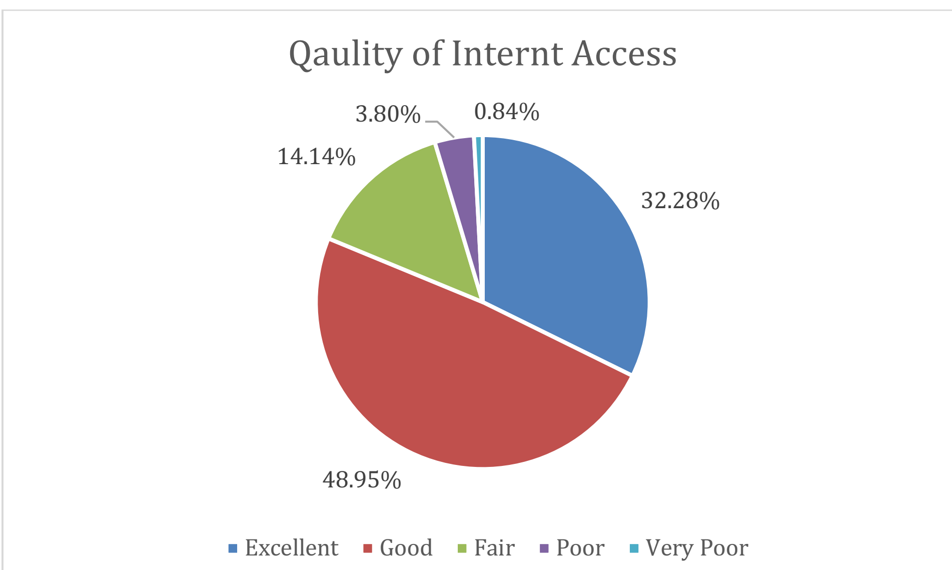

Figure 2. Quality of Internet Access

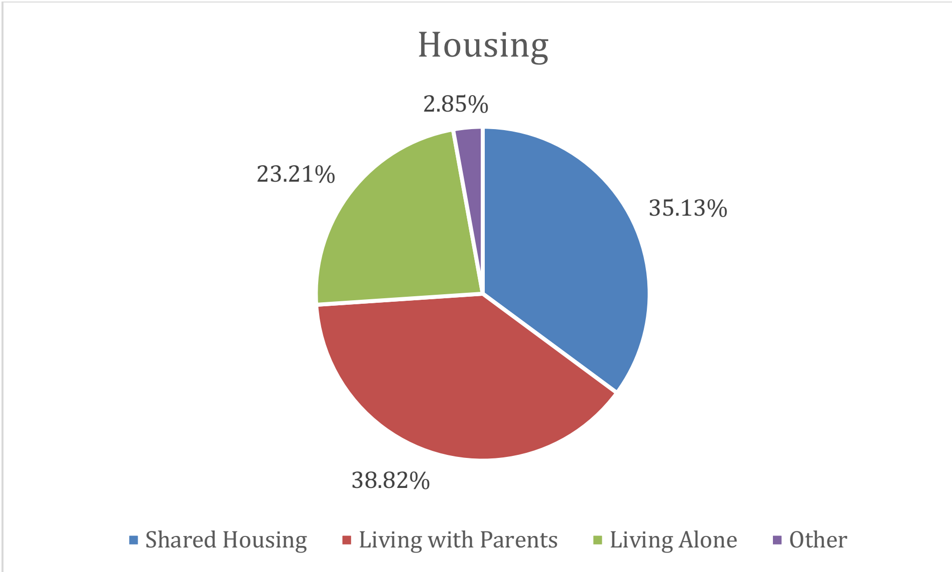

Figure 3. Housing

Regarding learning style and personality, 61.9% of students 'strongly agreed' or 'somewhat agreed' that their learning style was compatible with the e-learning system, while 19.05% 'neither agreed nor disagreed' and 19.05% 'strongly disagreed' or 'somewhat disagreed,' shown in in Figure 4. 61.9% of students 'strongly agreed' or 'somewhat agreed' that their personality naturally allowed them to work well with the e-learning system, while 9.52% 'neither agreed nor disagreed' and 28.57% 'strongly disagreed' or 'somewhat disagreed,' shown in in Figure 5.

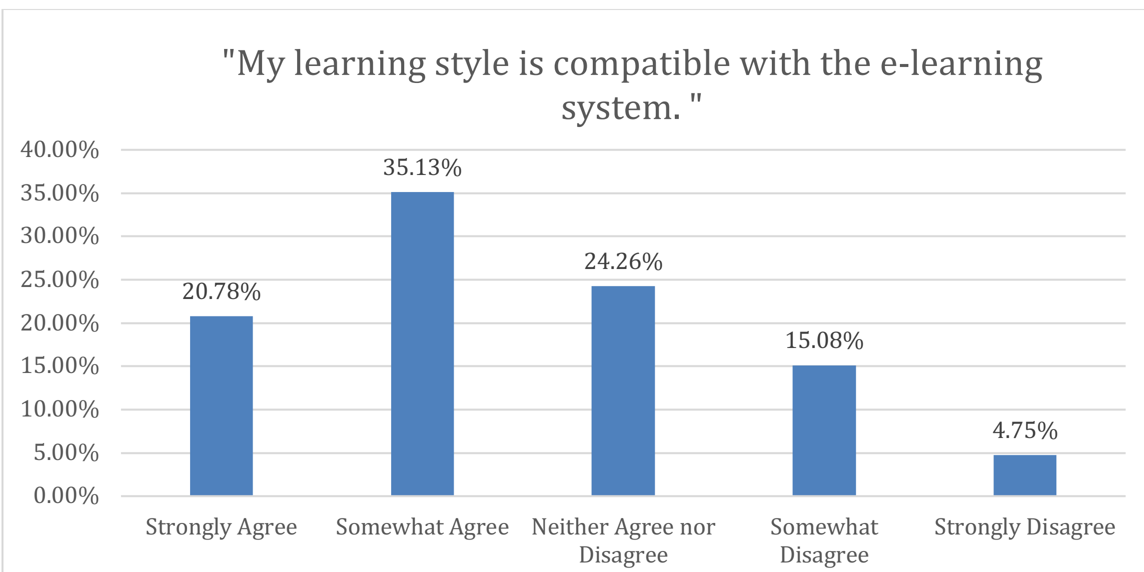

Figure 4. Learning Style Compatibility

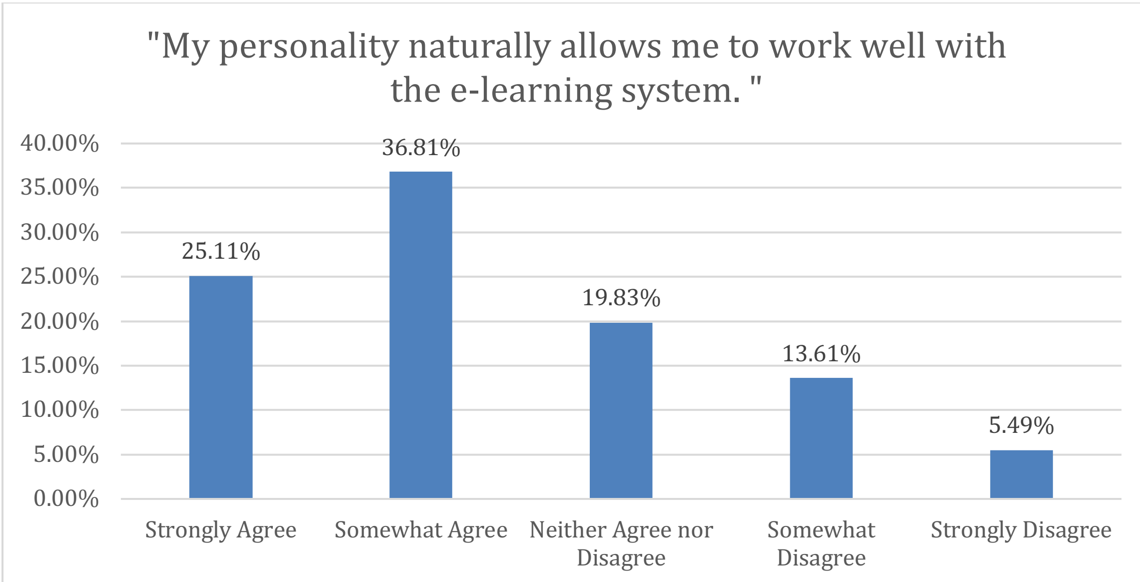

Figure 5. Personality Compatibility

ANOVA Analysis.

To understand the impact of background factors on the TAM model, series of ANOVA were conducted considering learning style, personality, GPA, housing, voluntariness, and quality of internet access as independent variables, and the TAM model factors including actual use, behavioral intention to use, perceived ease of use, and perceived usefulness as dependent variables.

The results from ANOVA showed that learning style and personality both had strongly significant relationships with every TAM factor, ($p<=0.000$). Quality of internet access had strongly significant relationships with behavioral intention to use and perceived ease of use with ($p<=0.000$) and significant relationships with actual use and perceived usefulness with ($p=0.001$).

GPA had a significant relationship with perceived usefulness ($p=0.001$) and a slightly significant relationship with actual use ($p=0.1$). Voluntariness had a significant relationship with actual use ($p=0.001$) and a significant relationship with perceived usefulness ($p=0.05$). Housing (where students lived while taking online classes) had no effect on any of the TAM factors. The detailed results of ANOVA testing are shown in Tables 2a-d.

Table 2a. ANOVA results between Actual Use and background factors. P-values and significance codes show significant relationships between factors.

ANOVA with Actual Use and Background Factors					
	Df	Sum Sq	Mean Sq	F-value	Pr(>F)
Learning Style	3	114.0	37.99	95.727	< 2e-16 ***
Personality	3	9.4	3.14	7.902	3.3e-05 ***
GPA	2	2.0	0.98	2.466	0.08551

Housing	2	0.2	0.11	0.274	0.76060
Voluntariness	1	3.2	3.21	8.097	0.00453 **
Quality of Internet Access	2	3.8	1.88	4.74	0.00895 **

Table 2b. ANOVA results between Behavioral Intention to Use and background factors. P-values and significance codes show significant relationships between factors.

ANOVA with Behavioral Intention to Use and Background Factors					
	Df	Sum Sq	Mean Sq	F-value	Pr(>F)
Learning Style	3	166.2	55.40	147.729	< 2e-16 ***
Personality	3	19.4	6.46	17.216	6.9e-11 ***
GPA	2	1.7	0.84	2.241	0.106884
Housing	2	0.3	0.15	0.409	0.664696
Voluntariness	1	0.4	0.44	1.163	0.281132
Quality of Internet Access	2	6.6	3.32	8.865	0.00153 ***

Table 2c. ANOVA results between Perceived Usefulness and background factors. P-values and significance codes show significant relationships between factors.

ANOVA with Perceived Usefulness and Background Factors					
	Df	Sum Sq	Mean Sq	F-value	Pr(>F)
Learning Style	3	195.2	65.06	160.005	< 2e-16 ***
Personality	3	20.4	6.81	16.738	1.34e-10 ***
GPA	2	3.8	1.92	4.715	0.00917 **
Housing	2	0.6	0.28	0.682	0.50600
Voluntariness	1	2.2	2.19	5.388	0.02049 *
Quality of Internet	2	4.9	2.46	6.056	0.00244 **

Access					

Table 2d. ANOVA results between Perceived Ease of Use and background factors. P-values and significance codes show significant relationships between factors.

ANOVA with Perceived Ease of Use and Background Factors					
	Df	Sum Sq	Mean Sq	F-value	Pr(>F)
Learning Style	3	131.8	43.94	114.267	< 2e-16 ***
Personality	3	12.6	4.20	10.933	4.63e-07 ***
GPA	2	1.0	0.49	1.278	0.27920
Housing	2	0.5	0.24	0.628	0.53387
Voluntariness	1	0.5	0.48	1.243	0.26516
Quality of Internet Access	2	5.4	2.72	7.077	0.00089 ***

Discussion.

The results of the ANOVA analysis showed that learning style, personality, and quality of internet access were the most statistically significant factors predicting actual use, behavioral intention to use, perceived usefulness, and perceived ease of use for Generation Z students using online learning technology during the COVID-19 pandemic. The three factors are discussed in this section. The other factors of GPA and Housing sometimes had significant relationships with the TAM factors, but not with the same strength that Learning Style, Personality, Quality of Internet Access, and Voluntariness have.

Learning style has been shown to influence students' acceptance of e-learning technology by impacting students' perceptions of online learning [20] and bettering their engagement with e e-learning systems [21], though other studies have found conflicting results [14]. In this study, ANOVA analysis showed that learning style had a significant impact on each of the TAM factors (Actual Use, Behavioral Intention to Use, Perceived Usefulness, Perceived Ease of Use), suggesting that Generation Z students' learning styles greatly impact their acceptance of e-learning, influencing both their perceived usefulness and ease of use, as well as their current system use and intention to use it in the future. Not many studies exist assessing the impact of students' learning styles on their use of e-learning technology, though this study, and several before it, show that this factor ought to be further explored in the future [14, 20-21].

In the literature, personality has similarly been shown to impact students' perceptions, use, and outcomes of e-learning systems [6-7, 13]. Yu, 2021 [7] specifically showed that personality had an impact on e-learning system use during the pandemic, with extraversion being negatively correlated with online learning outcomes, though the study did not analyze specifically Generation Z students. This study found that personality has an impact on Generation Z students' actual use of e-learning technology, having significant relationships with all TAM factors (Actual Use, Behavioral Intention to Use, Perceived Usefulness, Perceived Ease of Use).

Quality of Internet Access had statistically significant relationships with all the TAM factors (Actual Use, Behavioral Intention to Use, Perceived Usefulness, Perceived Ease of Use), with the strongest relationships being with Behavioral Intention to Use and Perceived Ease of Use. Voluntariness also had impacts on the TAM factors, though only on Actual Use and Perceived Usefulness, and with less statistical significance than personality, and learning style, and quality of internet access. These two factors face the same challenge as personality and learning style, though, as very few researchers have included these factors when studying student use of e-learning technology [18-19].

It is worth noting that GPA had similar relationships as Voluntariness, having an impact on Actual Use and Perceived Usefulness, though with less statistical significance. Housing had no statistically significant relationships with any of the TAM factors.

This study highlights the importance of several factors that ought to be explored in the future, as they have not been fully investigated in the literature. Part of this, however, may be due to the difficulty of defining personality, learning style, and quality of internet access, and voluntariness has usually been irrelevant to online learning studies, since students taking online classes most often do so by choice.

A limitation this study faces was the use of subjective measures and self-report tools. The survey in this study did not define personality or learning style for respondents using an existing measure, allowing respondents to use their own understanding of these factors to focus on what they believed the impact of their learning style and personality to be, rather than trying to define their learning style or personality. Attempting to define these highly individual traits is difficult, as it can be imprecise, and while many different scales exist to try to describe them, they often end up putting students in 'boxes,' when, in reality, students' personalities and learning styles may exist on a spectrum and change over time. However, the use of subjective measures invites the issue of every respondent answering the questions based on a different understanding of personality and learning style–in the future, studies need to incorporate both objective and subjective measures of these factors. This is an issue with the quality of internet access item as well.

Additionally, other studies have found previous experience with online courses to be an impactful factor in students' acceptance of online learning technology. While the survey used in this study did have an item asking about previous experience ("Have you taken at least three online courses before?"), the two levels ("yes" and "no") were too imbalanced to use in the analysis. This factor ought to be explored further with a more diverse sample group.

This study also only analyzed Generation Z students, most of whom were enrolled in universities in the United States, and though the sample included nearly 1000 responses, this is not enough to generalize the results to other groups, especially to other generations. This study also focused on the impact of COVID-19, a very specific context. Future studies can expand the sample group to include more diverse students.

This study found that the key factors impacting Generation Z students' use of e-learning technologies during the COVID-19 pandemic are personality, learning style, voluntariness, and quality of internet access. Designers of e-learning systems, e-learning practitioners, and other researchers ought to be aware of these factors when designing, using, and studying e-learning systems, especially when working with Generation Z students.

Conclusion.

The COVID-19 pandemic greatly disrupted students' daily lives, as universities were forced to rapidly switch to online learning to facilitate schooling while public places were closed. The rapid shift to distance learning left students with varied responses and levels of acceptance, as they were suddenly required to take their courses online; previously, most students taking courses online were doing so by choice, but now, even students who preferred in-person schooling had to be online [6-7, 9-13]. In addition to this, students faced additional challenges caused by the pandemic, from changes in housing and access to the internet to isolation and loss of social activities leading to increasing mental health concerns [3, 8, 15-16]. Students' individual differences, such as their learning styles, personalities, and other demographic variables may also impact their acceptance and use of e-learning technology. This study's goal is to understand the impact of Generation Z students' backgrounds on their acceptance and use of online learning technology.

To begin answering this question, this study used the Technology Acceptance Model, TAM, developed by Davis, 1989 [17]. TAM includes the factors of actual use, behavioral intention to use, perceived usefulness, and perceived ease of use to describe how users of a technology accept it. This framework has been used in many studies relating to online learning [4, 9, 13-14, 17-18].

This study created a survey asking after students' background, including their learning styles, personalities, GPA, housing, voluntariness of use, and quality of internet access, as well as the TAM factors. The survey received 1000 responses and was cleaned to have 948 valid responses. As a result, it was found that learning style, personality, and quality of internet access had statistically significant relationships with each of the TAM factors (Actual Use, Behavioral Intention to Use, Perceived Ease of Use, Perceived Usefulness), while voluntariness and GPA had significant relationships with Actual Use and Perceived Usefulness. Housing had no significant effect on any of the TAM factors. While these findings are supported with literature, this study expands on the impact of Generation Z students' backgrounds on their acceptance and use of e-learning technology during the COVID-19 pandemic. This study gives insightful information to program managers and new educators about how students' diverse origins influence their educational experiences. Such information is critical for the creation of new online based programs. In order to improve students' online learning experiences, new educators as well as program managers should give priority to resources and interventions that address the substantial links shown between learning style, personality, and quality of internet access, and students acceptance.

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