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Analysis of the attitudes of generation z prospective science teachers toward the chemistry virtual laboratory

Hilman Qudratuddarsi[*1], Nur Rahmah[1], Nor Indriyanti[1], Jumriani[1], Munawwarah[2]
[1]Science Education, Faculty of Teacher Training and Education, Sulawesi Barat University, Majene, Indonesia
[2]Chemisty Education, Faculty of Science, Makassar State University, Makassar, Indonesia
E-mail: hilman.qudratuddarsi@unsulbar.ac.id *

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ABSTRACT

Virtual laboratories are technological innovations that allow users to conduct chemistry experiments interactively without space, time, or material constraints. This study aims to analyze the attitudes of Generation Z prospective science teachers toward using virtual laboratories in chemistry learning by integrating the Theory of Planned Behaviour (TPB) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). A quantitative survey method was applied, involving 83 student respondents. The instrument was a questionnaire that measured performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, attitude, perceived behavioral control, and behavioral intention. The findings revealed a significant positive correlation between all independent variables, behavioral intention, and virtual laboratory usage. Habit and perceived behavioral control emerged as the most influential factors. This study provides valuable insights for developing strategies to integrate virtual laboratories into science teacher education based on Generation Z's technological preferences.

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1. INTRODUCTION

Laboratory activities are a fundamental component of science education, particularly in chemistry, where abstract concepts are often best understood through hands-on experimentation. For prospective science teachers, especially in the field of chemistry, practical work provides essential experiences that foster deep conceptual understanding, scientific inquiry skills, and the development of teaching competencies (Tantayanon et al., 2024). Engaging directly with chemical substances, equipment, and experimental procedures allows teacher candidates to connect theoretical knowledge with real-world applications (García-Torres, 2025). Moreover, practical experiments encourage the development of critical thinking, problem-solving, and the ability to design and assess experiments - skills that are imperative not only for their academic development but also for their future roles as educators in the field of science (Rahmah & Qudratuddarsi, 2024). Practical experiences also prepare future teachers to design meaningful laboratory instructions, manage classroom safety, and foster scientific attitudes in their students (Garcia et al., 2024). These competencies form the backbone of effective science teaching and are vital for enhancing the quality of science education in schools.

The study was conducted in a setting where traditional chemistry laboratories were either limited or insufficient. Most participants were enrolled in teacher education programs in rural or semi-urban campuses, where access to full-scale chemistry labs was constrained due to outdated infrastructure, minimal safety equipment, and irregular supply of chemicals. These constraints meant that practical work was often replaced with demonstrations or simulations. Therefore, the virtual laboratory served not only as an instructional innovation but also as a necessary substitute for hands-on lab experience. Participants accessed the virtual lab via their personal devices, often under conditions of varying internet connectivity and digital literacy, which further underscored the need to understand their attitudes and readiness toward virtual lab adoption. However, in many educational institutions, particularly in developing regions, the implementation of direct chemistry practicum faces various limitations. Among the most critical are inadequate laboratory facilities, limited access to materials and instruments, safety concerns, and financial constraints (Deriba et al., 2024). These barriers often lead to a reduction in the frequency and quality of laboratory sessions (Driana, 2025). In some cases, laboratory work is limited to demonstrations by instructors, depriving students of active participation and experiential learning (Toit & Toit, 2024). Moreover, maintaining physical laboratories requires continuous investment in chemicals, safety infrastructure, and maintenance of delicate instruments - all of which can be burdensome for institutions with restricted budgets (Bharadwaj & Verma, 2025). As a result, many students - especially those in teacher education programs - graduate with limited laboratory experience, thereby affecting their confidence and competence in conducting and teaching practical science (Kolil et al., 2020). This shortfall is concerning, given that these students will eventually be responsible for designing and implementing laboratory instruction in their future classrooms (Shambare & Jita, 2025).

In response to this challenge, virtual laboratories have emerged as a promising alternative. These digital platforms simulate laboratory environments and allow users to perform experiments interactively without the need for physical resources (Ali et al., 2022). Virtual labs offer significant benefits such as flexibility, repeatability, enhanced visualization of abstract concepts, and increased safety, making them a viable solution to complement or substitute traditional practicum in chemistry education (Dunstan, 2021). Students can conduct experiments multiple times, make mistakes without real-world consequences, and manipulate variables to observe different outcomes - all of which enhance their understanding and curiosity (Wörner et al., 2022). Furthermore, virtual labs can be accessed anytime and anywhere, making them highly compatible with distance learning and hybrid education models (Turakulova, 2025). From an institutional perspective, virtual labs can be cost-effective and scalable, enabling consistent laboratory experiences across different campuses or regions (Castro-Gutiérrez et al., 2021). These advantages make virtual laboratories not only a response to logistical constraints but also a forward-looking innovation in science education (Schiff, 2021).

The research specifically targeted Generation Z students, identified demographically as those born between 1997 and 2012. Their characteristics generation Z captured not only their technological fluency and preferences for interactive, digital learning environments but also their behavioral intentions, perceived enjoyment (hedonic motivation), and habitual technology use. These aspects reflect typical Gen Z traits—such as preference for autonomy, visual and experiential learning, and quick access to information—and how such traits manifest in the context of chemistry learning. By correlating Gen Z's psychological and behavioral traits with technology acceptance variables, the study provided a nuanced view of how this cohort engages with digital chemistry instruction tools. The potential of virtual laboratories is further reinforced by the characteristics of today's pre-service teachers, many of whom belong to Generation Z - a generation that has grown up with digital technology as an integral part of their daily lives. Gen Z individuals are typically described as digital natives who are highly comfortable using various forms of technology for learning, communication, and problem-solving (Lopez & Abadiano, 2023). Their familiarity with digital platforms, interactive tools, and virtual environments presents a unique opportunity for the integration of educational technology in teacher training (Yanti et al., 2023). Virtual laboratories, which combine interactive multimedia with simulated experimentation, align well with the learning preferences and digital fluency of Gen Z (O'Farrell & Weaver, 2024). This alignment suggests that virtual labs are not only a practical solution to logistical constraints but also a pedagogical tool that resonates with the cognitive styles and technological habits of modern students, especially future science educators (Yeganeh et al., 2025). Gen Z learners tend to prefer self-directed, visually engaging, and gamified learning experiences, all of which are often characteristics of high-quality virtual lab platforms (Shafiq et al., 2025).

In addition, Generation Z students often demonstrate a preference for learning tools that provide instant feedback, allow for personalization, and are integrated with mobile or web-based applications. This affinity positions virtual labs as a natural fit in their learning ecosystems (Glaser et al., 2021). However, despite their technological savviness, not all Gen Z students may automatically adopt or embrace educational technologies for academic purposes (Hernandez-de-Menendez et al., 2020). Attitudes, perceptions of usefulness, ease of use, and social influence continue to play important roles in determining whether they will engage with tools such as virtual laboratories (Du et al., 2022). Therefore, while the technological readiness of Gen Z is an enabler, it must be understood in conjunction with other psychological and contextual factors that shape behavior (Zamrudi et al., 2025). Investigating these factors becomes imperative in ensuring that virtual lab interventions are designed and implemented in ways that truly meet the needs and expectations of future science teachers (Zamrudi et al., 2025).

This study integrated the Theory of Planned Behavior (TPB) and Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) into a unified framework as shown in Figure 1 to capture both motivational and contextual determinants of virtual lab use. The combined model consists of: TPB Constructs: Attitude – individual's positive or negative evaluation of using the virtual lab, subjective Norms (mapped to Social Influence in UTAUT2), Perceived Behavioral Control – students' perception of their ability and resources to use the platform. And for UTAUT2 Constructs consists of Performance Expectancy, Effort Expectancy, Facilitating Conditions, Hedonic Motivation, and Habit. These variables collectively influence Behavioral Intention, which in turn predicts Actual Virtual Laboratory Use. The combination provides both psychological depth (via TPB) and contextual breadth (via UTAUT2). This framework is particularly suitable for Generation Z learners who operate within complex digital ecosystems where both internal attitudes and external supports influence technology engagement. UTAUT2, on the other hand, extends earlier technology acceptance models by incorporating constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and price value. These constructs offer a comprehensive lens through which the cognitive and contextual factors influencing technology adoption can be examined (Duan, & Dong, 2025). For example, performance expectancy reflects the degree to which a virtual lab is perceived as improving learning outcomes, while effort expectancy captures the perceived ease of its use. Hedonic motivation evaluates the enjoyment derived from the experience, which is particularly relevant for Gen Z learners. Facilitating conditions and habit assess the availability of institutional support and prior exposure to similar tools. When combined, TPB and UTAUT2 provide a powerful framework to explore the complex interplay of psychological and environmental factors that affect the intention of Gen Z teacher candidates to use virtual laboratory platforms. The dual application of these models allows for a richer, more nuanced understanding of the motivations and barriers to technology adoption in science teacher education (Selvi, & Önem, 2025).

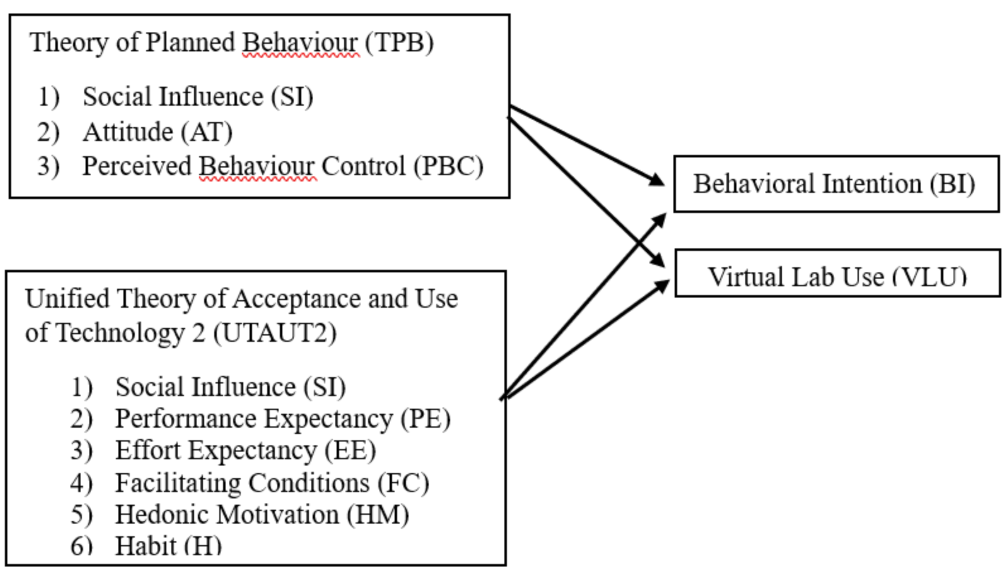

Figure 1. Theoretical framework

Despite the increasing availability of virtual laboratories and the growing body of literature on technology acceptance in education, there remains a research gap in understanding the specific attitudes and behavioral intentions of Generation Z science teacher candidates toward this technology. Existing studies have predominantly focused on students in general or teachers in service, with limited emphasis on pre-service teachers in the science domain. The unique position of pre-service teachers—who are both learners and future educators—places them at the intersection of technology adoption and pedagogical responsibility, yet this population remains underrepresented in empirical research. Furthermore, most studies examining technology acceptance in educational contexts tend to use either TPB or UTAUT2 in isolation, thereby overlooking the complementary strengths of each framework. Few studies have employed an integrated theoretical approach that combines TPB and UTAUT2 to capture both motivational and contextual factors influencing technology use in chemistry practicum. As a result, there is a lack of empirical evidence that could inform educational institutions, curriculum developers, and policy-makers on how best to design and implement virtual laboratory programs that are aligned with the needs, preferences, and technological readiness of this unique learner group.

In addition, much of the existing research has been conducted in Western or urban contexts, where access to digital infrastructure is relatively high. Little is known about how these dynamics play out in more diverse or resource-constrained environments. This raises further questions about equity, accessibility, and the role of institutional support in mediating the use of virtual laboratories. Understanding how Gen Z pre-service teachers in varied socio-economic and educational settings engage with such technology is crucial for ensuring inclusive and effective science education reform. Addressing this gap can also provide insights into how technology can be leveraged not just as a tool for learning, but as a transformative medium for teacher preparation.

Given these considerations, this study seeks to analyze the attitudes of Generation Z pre-service science teachers toward the use of virtual laboratories in chemistry education by applying the integrated frameworks of TPB and UTAUT2. This research is expected to contribute to the literature by filling the existing gap in theoretical and contextual understanding, and by offering practical insights into how virtual laboratory environments can be more effectively adopted in teacher education programs. It is also anticipated that the findings will help in designing more targeted strategies for integrating educational technology in science education that align with the digital dispositions of future educators. Furthermore, by leveraging the combined power of TPB and UTAUT2, This study was conducted based on the following research questions: Is there any positive and strong correlation between performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, attitude, perceived behavioral control toward behavioral intention, and virtual laboratory use.

2. METHODS

A. Research Design

The quantitative approach provided a structured and objective framework for data interpretation, allowing for the identification of significant patterns and correlations. This methodological choice was aligned with the research's broader goal—to generate generalizable findings that could inform the integration of virtual laboratories in teacher education curricula. This study adopted a quantitative survey design, emphasizing the systematic collection and statistical analysis of numerical data obtained through participant responses (Ghanad, 2023; Rana et al., 2020). Characterized as a survey, the research sought to capture the perceptions of pre-service science teachers regarding the use of virtual laboratories in chemistry instruction at a single point in time, without manipulating any inherent characteristics of the sample (Koca & Kizilay, 2024; Simanjuntak et al., 2024). The cross-sectional nature of this design enabled a focused examination of participants' attitudes and beliefs, offering a snapshot of their views in the current educational context (Lim, 2024). By limiting the scope to a specific moment, the study minimized the complexities typically associated with longitudinal designs, such as participant attrition and the influence of temporal or external variables.

The quantitative approach provided a structured and objective framework for data interpretation, allowing for the identification of significant patterns and correlations. This methodological choice was aligned with the research's broader goal—to generate generalizable findings that could inform the integration of virtual laboratories in teacher education curricula (Knekta et al., 2019).

B. Participants

A total of eighty-three Generation Z pre-service science teachers participated in the study, engaging in virtual laboratory-based experimentation. This sample group was particularly relevant, as many of the participants had minimal exposure to hands-on science experiments during their secondary education. Their experiences thus offered valuable insights into the perceived effectiveness and usability of virtual laboratories in compensating for traditional laboratory limitations.

Participants were recruited through convenience sampling, with the consideration that research could be carried out effectively and efficiently as they were students enrolled in courses taught by the researchers (Nur Rahmah, 2023). While this sampling method facilitated ease of access and data collection, it also introduced potential limitations concerning the generalizability of the findings, as the sample may not be fully representative of the wider population of pre-service science educators (Sullivan, 2012).

As presented in Table 1, the demographic composition of the sample was predominantly female (85.54%), with male participants comprising only 14.46%. Most respondents were aged either 18 or 19, reflecting the typical age range of undergraduate teacher trainees. These demographic details offer contextual information that aids in interpreting the findings, particularly given the study's focus on Generation Z—a cohort recognized for its digital fluency and familiarity with technological tools, which may shape their attitudes toward virtual learning environments.

Table 1. Distribution of pre-service science teachers by gender and age

Sample	N	Percentage
Gender		
Male	12	14.46 %
Female	71	85.54 %
Age		
18 years old	37	44.58 %
19 years old	46	55.42 %
Total	83	100 %

C. Instrument

The primary instrument utilized in this research was adapted from an established tool previously developed by Habibi et al., (2024) which explored users' acceptance of ChatGPT—a technology-integrated educational platform. Given that the instrument was already available in Bahasa Indonesia and had been published in high-impact academic journals, translation was unnecessary, thereby preserving the semantic integrity and contextual relevance of the original items. The instrument was deemed suitable for this study due to its grounding in prominent technology acceptance models, particularly the Unified Theory of Acceptance and Use of Technology (UTAUT), which closely aligns with the study's aim to examine virtual laboratory integration within science education.

To enhance content validity, the adapted instrument was reviewed by two subject-matter experts in science education assessment. Their feedback helped ensure that the instrument accurately captured constructs relevant to the target population of pre-service teachers and was appropriate for evaluating technology use in the context of virtual chemistry experiments.

The questionnaire have 37 items comprised several key constructs, each reflecting a different dimension of technology adoption: 1) Performance Expectancy (4 items), 2) Effort Expectancy (4 items), 3) Social Influence (3 items), 4) Facilitating Conditions (4 items), 5) Hedonic Motivation (4 items), 6) Habit (5 items), 7) Attitude (4 items), 8) Perceived Behavioral Control (3 items), 9) Behavioral Intention (BI), and 10) Virtual Laboratory Use (VLU). Together, these constructs provided a comprehensive framework for assessing the perceptions and acceptance of virtual laboratories among future science educators. The use of a well-validated, theory-driven instrument contributed to the methodological robustness of the study.

D. Data Collection Procedure

Data collection was conducted electronically via Google Forms, reflecting the study's commitment to environmentally conscious practices by reducing paper use. The online platform facilitated efficient data management, streamlined organization, and minimized the potential for manual data entry errors. To ensure data quality and participant comprehension, the researcher personally supervised the administration of the instrument. Participants were allowed to seek clarification on any survey item, thus reducing misinterpretation and enhancing the reliability of the responses. This direct engagement also created a supportive environment conducive to thoughtful and accurate participation. Participation in the study was entirely voluntary, and students were informed that their involvement would not influence their academic standing or grades. Additionally, the confidentiality of their responses was emphasized to promote honesty and reduce social desirability bias. These ethical considerations were essential for maintaining the study's integrity and ensuring that the data accurately reflected participants' genuine attitudes and experiences with virtual laboratory tools.

E. Data Analysis

Once all the respondents had completed giving their answers, the questionnaires were gathered. The data were first tabulated using Microsoft Excel for initial organization and cleaning. Subsequently, SPSS 25.0 was used to perform descriptive statistical analysis, including calculations of mean, median, mode, standard deviation, skewness, and kurtosis to understand the distribution and central tendencies of the variables. Following this, Pearson correlation analysis was conducted to assess the strength and direction of linear relationships between the variables. Pearson's correlation coefficient was used to determine how strongly pairs of variables are related (Schober & Schwarte, 2018). Later, the frequencies and percentages for each question were presented in tables, and they were described and discussed.

3. RESULTS AND DISCUSSIONS

This study analyze the correlation of PE (Performance Expectancy), EE (Effort Expectancy), SI (Social Influence), FC (Facilitating Conditions), HM (Hedonic Motivation), H (Habit), VL (Value), BI (Behavioral Intention), PBC (Perceived Behavioral Control), and AT (Attitude) toward Behavioral Intention (BI) and Virtual Laboratory Use (VLU). The descriptive statistics (Table 1) provides a comprehensive overview of the central tendency, dispersion, and distribution shape for each of the variables measured in the dataset.

Table 2. Descriptive statistics

	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
Variable	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Std. Error**	**Statistic**	**Std. Error**
PE	1.00	5.00	3.9177	1.06834	-.914	.264	.187	.523
EE	1.00	5.00	3.8567	1.08939	-.822	.266	.072	.526
SI	1.00	5.00	3.5885	1.03182	-.568	.267	.136	.529
FC	1.00	5.00	3.7901	1.07198	-.777	.267	.180	.529
HM	1.00	5.00	3.8560	1.19831	-.757	.267	-.390	.529
H	1.00	5.00	3.6476	.97144	-.492	.266	.428	.526
PBC	1.00	4.67	2.9438	.84073	-.104	.264	-.363	.523
AT	1.50	4.50	3.0572	.70746	-.024	.264	-.564	.523
VLU	1.00	5.00	3.5904	.98268	-.358	.264	-.028	.523
BI	1.00	5.00	3.7982	1.05016	-.576	.264	-.137	.523

In terms of central tendency, the mean scores show that most constructs hover around the mid-to-high point of the scale. For instance, Performance Expectancy (PE) has a mean of 3.92, suggesting that respondents generally agree with the statements regarding expected performance improvements. Similar trends are observed for EE (3.86), FC (3.79), HM (3.86), and BI (3.80), all indicating relatively favorable responses toward technology use or behavioral intention. On the other hand, PBC (2.94) and AT (3.06) show lower means compared to other variables, suggesting a more neutral or uncertain perception of control and attitude.

Specially for respondents generally rated Perceived Behavioral Control (PBC) neutrally to slightly positively, with a mean of 2.94, which is just below the mid-point of the 5-point Likert scale. There was moderate variation in responses. The distribution was fairly symmetrical and slightly flat, indicating that most respondents clustered around the average score. This suggests that while some Gen Z teacher candidates feel confident in using virtual laboratories, many may still feel uncertain or lack the perceived resources, skills, or autonomy, which could be a barrier to full adoption.

The standard deviation values, ranging from 0.71 (AT) to 1.20 (HM), show moderate variation in responses. A higher standard deviation indicates more diverse opinions among respondents. For instance, the relatively high deviation for Hedonic Motivation suggests that while some respondents found the system enjoyable, others did not share this view.

Skewness values help assess the symmetry of the data distribution. All variables show negative skewness, indicating a slight tendency for responses to be skewed toward the higher end of the scale (positive perceptions). For example, PE has a skewness of -0.914, implying that many respondents gave higher ratings for performance expectancy. However, the magnitude of skewness is within acceptable limits (typically between -1 and +1), suggesting that the distributions are not severely skewed. Kurtosis, which measures the "tailedness" of the distribution, generally falls between -0.56 and +0.43 across variables, all close to zero. This suggests that most variables follow a distribution shape that is fairly similar to the normal distribution. None of the constructs exhibit extreme kurtosis, which is favorable for analyses assuming normality for correlational analysis.

The data presents descriptive statistics on respondents' levels of agreement with a series of Likert-scale survey items across multiple constructs, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (H), Attitude Toward Using Technology (AT), Perceived Behavioral Control (PBC), Behavioral Intention (BI), and Value (VL). Each item was rated on a 5-point scale from "Very Disagree" to "Very Agree." The results provide insight into user perceptions and behavioral inclinations towards technology or system adoption, likely within the context of the Unified Theory of Acceptance and Use of Technology (UTAUT2) or a similar model.

Overall, the majority of respondents expressed agreement or strong agreement across most items, suggesting generally positive perceptions. For instance, items such as PE1, BI2, and HM1 show high rates of agreement (over 60%), indicating strong perceived performance benefits, behavioral intent, and hedonic motivation. Conversely, items like AT2 and PBC3 exhibit relatively high levels of disagreement (over 40%), hinting at resistance or uncertainty toward attitude and perceived control. Neutral responses are also notable in items such as H3 and VL3, indicating possible ambivalence. Social Influence (SI) items have more distributed responses, suggesting mixed views on peer effects. In sum, while users tend to favor adopting the technology, concerns related to control, habit formation, and attitudes may hinder full adoption. These insights can guide targeted interventions to strengthen weak areas and reinforce positive perceptions.

Table 3. Item analysis of respondent

Item	**Likert Scale**									
	Very Disagree		**Disagree**		**Neutral**		**Agree**		**Very Agree**	
	n	**(%)**	**n**	**(%)**	**n**	**(%)**	**n**	**(%)**	**n**	**(%)**
PE1	6	7.23	2	2.41	15	18.07	17	20.48	43	51.81
PE2	3	3.61	8	9.64	18	21.69	23	27.71	31	37.35
PE3	4	4.82	4	4.82	21	25.30	20	24.10	34	40.96
PE4	5	6.02	1	1.20	26	31.33	19	22.89	32	38.55
EE1	7	8.43	5	6.02	16	19.28	18	21.69	37	44.58
EE2	6	7.23	7	8.43	18	21.69	14	16.87	38	45.78
EE3	4	4.82	3	3.61	23	27.71	24	28.92	29	34.94
EE4	3	3.61	4	4.82	26	31.33	25	30.12	25	30.12
SI1	6	7.23	5	6.02	23	27.71	26	31.33	23	27.71
SI2	8	9.64	5	6.02	30	36.14	23	27.71	17	20.48
SI3	8	9.64	5	6.02	24	28.92	27	32.53	19	22.89
FC1	7	8.43	9	10.84	20	24.10	17	20.48	30	36.14
FC2	4	4.82	2	2.41	23	27.71	28	33.73	26	31.33
FC3	6	7.23	4	4.82	23	27.71	21	25.30	29	34.94
FC4	7	8.43	4	4.82	17	20.48	22	26.51	33	39.76
HM1	6	7.23	7	8.43	18	21.69	16	19.28	36	43.37
HM2	4	4.82	9	10.84	19	22.89	17	20.48	34	40.96
HM3	5	6.02	5	6.02	21	25.30	17	20.48	35	42.17
H1	4	4.82	7	8.43	32	38.55	23	27.71	17	20.48
H2	4	4.82	5	6.02	28	33.73	23	27.71	23	27.71
H3	5	6.02	5	6.02	31	37.35	22	26.51	20	24.10
H4	4	4.82	5	6.02	28	33.73	23	27.71	23	27.71
H5	3	3.61	6	7.23	24	28.92	23	27.71	27	32.53
AT1	14	16.87	14	16.87	13	15.66	20	24.10	22	26.51
AT2	18	21.69	22	26.51	15	18.07	14	16.87	14	16.87
AT3	13	15.66	15	18.07	16	19.28	18	21.69	21	25.30
AT4	21	25.30	18	21.69	9	10.84	18	21.69	17	20.48
PBC1	20	24.10	14	16.87	21	25.30	15	18.07	13	15.66
PBC2	14	16.87	18	21.69	12	14.46	28	33.73	11	13.25
PBC3	23	27.71	11	13.25	15	18.07	19	22.89	15	18.07
BI1	4	4.82	5	6.02	23	27.71	22	26.51	29	34.94
BI2	7	8.43	2	2.41	24	28.92	16	19.28	34	40.96
BI3	4	4.82	4	4.82	29	34.94	19	22.89	27	32.53
BI4	4	4.82	2	2.41	28	33.73	21	25.30	28	33.73
VL1	5	6.02	9	10.84	28	33.73	23	27.71	18	21.69
VL2	5	6.02	8	9.64	26	31.33	24	28.92	20	24.10
VL3	4	4.82	2	2.41	34	40.96	18	21.69	25	30.12

Correlation analysis is conducted to identify and evaluate the strength and direction of linear relationships between the variables used in this study. This analysis utilizes Pearson's correlation coefficient, which measures the degree to which two variables correlated. Detailed correlation value of Independent Variable ((PE (Performance Expectancy), EE (Effort Expectancy), SI (Social Influence), FC (Facilitating Conditions), HM (Hedonic Motivation), H (Habit), VL (Value), BI

(Behavioral Intention), PBC (Perceived Behavioral Control), and AT (Attitude)) and Dependent Variable (Behavioral Intention (BI) and Virtual Laboratory Use (VLU).

Table 4 presents the correlation values between eight independent variables and two dependent variables: Behavioral Intention and Virtual Laboratory Use. The analysis reveals strong and statistically significant positive correlations across all variables, suggesting meaningful relationships between theoretical constructs and the adoption of virtual laboratory technology. These findings are examined within the frameworks of the Theory of Planned Behavior (TPB) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), both of which provide comprehensive explanations for user behavior in technology adoption.

Table 4. Correlation value of each variable

No.	Independent Variable	Dependent Variable	
		Behavioral Intention	**Virtual Laboratory Use**
1	Performance Expectancy	.880**	.801**
2	Effort Expectancy	.904**	.815**
3	Social Influence	.902**	.880**
4	Facilitating Conditions	.873**	.836**
5	Hedonic Motivation	.866**	.701**
6	Habit	.905**	.899**
7	Attitude	.835**	.876**
8	Perceived Behavioral Control	.911**	.793**

The Theory of Planned Behavior (TPB) posits that Behavioral Intention is the most immediate predictor of behavior, influenced by three core components: Attitude toward the behavior, Subjective Norms (SN), and Perceived Behavioral Control (PBC). This theory emphasizes the psychological processes behind decision-making and behavior performance.

On the other hand, UTAUT2 expands upon earlier technology acceptance models by including additional constructs that affect both Behavioral Intention and technology use behavior. The UTAUT2 model includes Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (H), and Price Value (the latter not included in this study). UTAUT2 is especially useful in capturing user experiences in voluntary and consumer-based contexts, such as educational technologies.

Social Influence, a key component in both TPB (as Subjective Norm) and UTAUT2, shows a very strong correlation with both Behavioral Intention (r = .902) and Virtual Laboratory Use (r = .880). This underscores the role of peer pressure, instructor expectations, and societal norms in shaping students' intentions and behaviors. In academic settings, the influence of friends, teachers, or institutional requirements can heavily affect a student's decision to use educational technologies. Performance Expectancy refers to the degree to which students believe that using the virtual laboratory will improve their academic performance. The correlation values are r = .880 with Behavioral Intention and r = .801 with actual usage. These strong relationships reflect that students are more likely to adopt and use virtual labs if they perceive them as effective tools for enhancing learning outcomes. This aligns with UTAUT2, where PE is considered the strongest determinant of user intention.

Effort Expectancy, or the perceived ease of use, correlates r = .904 with Behavioral Intention and r = .815 with Virtual Laboratory Use. This suggests that students are more likely to intend to use and actually engage with the virtual lab if they find the system easy to navigate and interact with. Ease of use is especially important in educational environments where technological anxiety or unfamiliarity could hinder adoption. Facilitating Conditions represent the degree to which students feel that the necessary resources, infrastructure, and support are available to use the technology. The correlations of r = .873 with Behavioral Intention and r = .836 with Virtual Laboratory Use confirm that external support factors—such as training, technical help, and reliable access—play a crucial role in students' use of virtual learning environments. This is consistent with UTAUT2, where FC directly influences both intention and actual use.

Hedonic Motivation refers to the fun or enjoyment derived from using technology. In this study, it shows a high correlation with Behavioral Intention (r = .866) and a moderate but still significant correlation with usage (r = .701). This finding supports the notion that students are more likely to adopt and use educational technology when they find it engaging or enjoyable—highlighting the importance of interactivity and user-centered design in virtual learning tools. Among all variables, Habit demonstrates the strongest correlations: r = .905 with Behavioral Intention and r = .899 with Virtual Laboratory Use. In UTAUT2, habit plays a crucial role, especially in long-term and repeated behavior patterns. These results imply that when students develop routines or familiarity with the virtual lab platform, they are more inclined to continue using it. Habit can also reduce cognitive load and decision-making effort, making continued usage more seamless.

Attitude, a TPB construct, is often seen as a user's overall evaluation of the behavior. It shows strong correlations with both Behavioral Intention (r = .835) and Virtual Laboratory Use (r = .876). A positive attitude towards virtual laboratories likely results from previous positive experiences, perceived usefulness, and perceived ease of use, supporting both TPB and UTAUT2's emphasis on user perceptions. PBC, a TPB component, is significantly correlated with Behavioral Intention (r = .911) and with usage (r = .793). This finding suggests that when students feel in control of their ability to use the technology—whether due to skills, resources, or confidence—they are more likely to intend and proceed to use it. This also reinforces the importance of technical support and training in educational technology deployment.

Despite offering valuable insights, this study has several limitations that may affect the interpretation and generalizability of its findings. The use of convenience sampling, involving students from the researchers' own courses, introduces potential selection bias and limits representativeness. With a modest sample size of 83 and a gender imbalance skewed toward female participants, the results may not reflect the broader demographic of pre-service science teachers. Additionally, the cross-sectional design captures only a single moment in time, restricting causal conclusions and omitting changes in perception or behavior. All data were self-reported, making them vulnerable to social desirability bias and response inaccuracies, despite supervision during administration. Although the instrument was adapted from a validated tool based on the UTAUT model, its original context—ChatGPT—differs from virtual laboratories, which could influence item interpretation. Furthermore, the absence of longitudinal or experimental data limits assessments of long-term impact, and unexamined factors such as digital access and literacy may also have shaped user perceptions.

4. CONCLUSIONS

This study explored the attitudes of Generation Z prospective science teachers toward the use of virtual laboratories in chemistry education by employing the integrated frameworks of TPB and UTAUT2. The results indicated that all measured variables—including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, attitude, and perceived behavioral control—had significant positive correlations with both behavioral intention and virtual laboratory use. Among these, habit and perceived behavioral control emerged as the most influential factors, highlighting the importance of routine engagement and a sense of autonomy in technology adoption. These findings suggest that virtual laboratories are well-received by digital-native learners and hold strong potential to enhance science teacher education. Therefore, institutions should consider incorporating virtual laboratory experiences into their curricula, supported by adequate infrastructure and training, to foster more effective, accessible, and engaging science learning environments for future educators.

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