The Effects of Smart campus (SC) on Students' Self-Directed Learning (SDL) and Attitudes toward Learning (ATL)

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Abstract
This study examines the effect of Smart Campus (SC) technologies on students' Self-Directed Learning (SDL) and Attitudes toward Learning (ATL) at Irbid National University (INU). The research was conducted on a sample of 362 students from different faculties at INU, selected through stratified random sampling during the first semester of the 2024/2025 academic year. To collect data, two adapted surveys were utilized: the SDL Readiness Scale and an ATL questionnaire. The study employed a quantitative research design and explanatory methods. Data analysis was performed using the Statistical Package for the Social Sciences (SPSS), where means, standard deviations, and ANOVA tests were calculated to evaluate the level of impact. The findings reveal that SC technologies significantly enhance students' SDL and ATL at a very high level. Gender did not show a significant influence on SDL or ATL, while academic achievement had a notable effect on SDL. Students with higher academic performance exhibited stronger SDL skills, though no substantial variation in ATL was found across different academic achievement levels. This study underscores the critical role of SC technologies in promoting SDL and ATL, highlighting the need for further investigation into their impact on student learning outcomes in higher education.

Keywords: Smart campus, Self-Directed Learning, Attitudes toward Learning.

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تأثير تقنيّات الحرم الجامعي الذكي على التعلم الذاتي للطلبة واتجاهاتهم نحو التعلم

الملخص

تهدف هذه الدراسة إلى الكشف عن تأثير تقنيات الحرم الجامعي الذكي على التعلم الذاتي للطلاب، واتجاهاتهم نحو التعلم في جامعة إربد الأهليّة جُمعت البيانات من عينة مكونة من 362 طالبًا في الفصل الدراسي الأول من العام الأكاديمي 2025/2024 باستخدام استبانتين معدلتين، هما: استبانة مقياس استعداد التعلم الذاتي، واستبانة اتجاهات نحو التعلم. استخدمت الدراسة المنهج المسحي الكمي، وحُلّلت البيانات باستخدام الحزمة الإحصائية للعلوم الاجتماعية (SPSS)، حيث استخرجت المتوسطات الحسابية، والانحرافات المعيارية، واختبار تحليل التباين (ANOVA) لتقييم مستوى التأثير. أظهرت النتائج أن الحرم الجامعي الذكي يعزز بشكل كبير كلاً من التعلم الذاتي، واتجاهات التعلم بمستوى عالٍ جدًا. لم يظهر تأثير كبير للجنس على التعلم الذاتي، أو اتجاهات التعلم، في حين كان لمستوى التحصيل الأكاديمي تأثير ملحوظ على التعلم الذاتي. أظهر الطلاب الذين لديهم تحصيل أكاديمي أعلى مهارات تعلم ذاتي أقوى، رغم أنه لم يُلاحظ أي اختلافات ذات دلالة إحصائية في اتجاهات التعلم عبر مستويات التحصيل الأكاديمي. تؤكد الدراسة أهمية الحرم الجامعي الذكي في تعزيز التعلم الذاتي واتجاهات التعلم، وتدعو إلى المزيد من البحوث حول دوره في تشكيل نتائج الطلاب في التعليم العالي.

الكلمات المفتاحية: الحرم الجامعي الذكي، التعلم الذاتي، اتجاهات نحو التعلم.

Introductions

Education is an ongoing process that continuously evolves with the world. As societies progress, the methods through which educational content is delivered have seen significant transformations. Technological advancements have played a crucial role in shaping how education is presented. Historically, from early education to higher education, learning has been largely manual, involving direct, physical interaction between teachers and students. This traditional approach allowed for face-to-face communication and a more personal exchange of knowledge (Kan’an et al., In press). However, recent technological innovations have transformed many aspects of daily life, including the field of education (Pattnayak et al., 2024; Saritas et al., 2022). In response to the digital age, educational institutions have sought ways to adapt, leading to the rise of the "smart campus" concept. This innovative model aims to improve the learning experience and enhance the overall efficiency of educational systems (Polin et al., 2023).

Background

While the idea of a "smart campus" (SC) has gained considerable attention, challenges remain, particularly regarding inadequate system integration in the digital transformation of universities and colleges (Chai, 2025). A SC utilizes advanced technologies to develop an intelligent environment that efficiently connects physical infrastructure, data analytics, and digital connectivity. This integration enhances educational processes, improves student experiences, and streamlines administrative functions (Valaskova et al., 2022).

The foundation of SC is built on the integration of internet of things devices and sensors, which facilitate real-time data collection and analysis (Alhamed, 2022; Lu & Wu, 2022). These technologies are strategically deployed across various campus locations, including classrooms, laboratories, libraries, dormitories, and other essential spaces. By monitoring factors such as energy consumption, occupancy, and temperature, educational institutions can gain critical insights to enhance resource management, improve facility operations, and promote sustainability (Wang et al., 2023).

Smart campuses (SC) support various educational applications, including adaptive learning, virtual classrooms and teacher evaluation. Analyzing the influence of technology on education reveals that it significantly enhances both instructional quality and student learning outcomes (Alam, 2022).

SC technologies have the potential to transform administrative processes within educational institutions (Silva-da-Nóbrega et al., 2022). Automated systems powered by artificial intelligence can streamline tasks such as course registration, scheduling, and campus service management (Salau et al., 2022). This not only enhances operational efficiency but also allows administrative staff to focus on strategic initiatives and student support. Furthermore, SC solutions contribute to improved security measures, helping to ensure the safety and well-being of both students and staff (Gupta &

Gaurav, 2023). Also, SC enhances both the learning experience and administrative efficiency (Tyagi, et al., 2024).
Despite their benefits, implementing SC technologies comes with challenges. The collection and analysis of sensitive data raise concerns about privacy and ethical considerations. To safeguard student information, educational institutions must prioritize data security and establish robust protection measures. Additionally, the financial impact and return on investment must be carefully evaluated to ensure the cost-effectiveness of these technological advancements (Smuha, 2022).
Self-Directed Learning (SDL) is an approach in which individuals take initiative, either independently or with guidance, to assess their learning needs, set objectives, identify resources (both human and material), select and apply suitable learning strategies, and evaluate outcomes (Lee, 2010). In the context of education, SDL encourages learners to become independent, mature, and self-motivated in their learning journey (Savin-Baden & Major, 2004). This approach enhances academic performance, strengthens problem-solving abilities, and promotes teamwork as well as essential social skills like communication. Additionally, SDL increases student satisfaction with their curriculum and makes the learning process more engaging (Ahlam & Gaber, 2014; Ding et al., 2014).

Significance of the study
The campus environment plays a significant role in influencing students' motivation to learn. A positive and supportive campus atmosphere can enhance motivation, which, in turn, can lead to improved academic performance. A conducive environment involves fostering strong relationships among students, as well as between students and lecturers (Naibaho et al., 2010).
Given the widespread adoption of SC globally, stakeholders need a deeper understanding of how SC impacts education. The findings from this study will provide valuable insights that contribute to the broader body of knowledge in the education sector. These results will shed light on how SC affects students, helping stakeholders make informed decisions about the integration or use of SC technologies. With this information, stakeholders will be better equipped to make educated decisions at the individual, policy, and educational levels. The outcomes will significantly support or challenge the adoption of SC in universities, regions, and globally. Furthermore, this data will be essential for government agencies and policymakers, offering them the necessary tools and information to guide budgetary and policy decisions related to the implementation and investment in SC.
The intrinsic and extrinsic motivation theory suggests that motivation can originate from either internal factors or external influences (Tohidi & Jabbari, 2012). According to the intrinsic theory of motivation, a person's drive comes from within, as they engage in activities for personal fulfillment rather than external rewards. This is an example of an internal locus of control, where

individuals are motivated to achieve goals for their benefit, without needing external pressure. The motivation originates internally, serving as a powerful force that encourages action without external compulsion (Cook & Artino, 2016).

A student's Attitudes toward learning (ATL) are a crucial internal factor that fuels their self-motivation. On the other hand, extrinsic motivation suggests that external factors, such as rewards, punishments, or external pressure, serve as the source of motivation. While extrinsic motivation can be a powerful initial driving force, it may spark a student's interest in learning, even before they fully recognize their intrinsic motivations, which ultimately guide them toward achieving their desired goals.

Research Problem

The rapid advancement of educational technology has led to the creation of Smart Campus (SC) environments, which integrate digital tools and automated systems to enhance the learning experience. While SC technologies are designed to improve student engagement, streamline administrative processes, and support personalized learning, their direct impact on students' Self-Directed Learning (SDL) and Attitudes Toward Learning (ATL) is still not well understood.

Despite the increasing implementation of SC technologies in higher education institutions, there is a lack of empirical evidence regarding how these innovations affect students' initiative in their learning (SDL) and their overall perceptions of education (ATL). Given the global shift toward digital transformation in education, it is essential for educators, policymakers, and university administrators to understand how effective SC technologies are in fostering SDL and shaping ATL. This study addresses these gaps by investigating the impact of SC technologies on students' SDL and ATL at Irbid National University.

Purpose of the study

The goal of this study is to explore the various aspects of Smart campus (SC) technologies within the educational setting. By thoroughly examining the potential benefits and challenges associated with integrating SC into higher education institutions, this research aims to offer a comprehensive understanding. Through a detailed investigation of the research questions and objectives, the study seeks to provide valuable insights and recommendations to educators, administrators, and policymakers as they navigate the evolving landscape of SC technologies and their impact on the future of education. Specifically, this study will focus on evaluating the effects of SC on students' self-directed learning (SDL) and their attitudes toward learning (ATL) at INU.

To achieve this goal, the study will address the following research questions:

1. Does SC enhance students' SDL?
2. Does students' gender and academic achievement level influence their SDL?
3. Does SC positively affect students' attitudes toward learning?
4. Does students' gender and academic achievement level influence their attitudes at ATL?

The Connectional and Practical Definitions
1.Smart campus (SC):

This means that universities transition into digital environments by implementing robust digital platforms for teaching and learning, such as online open courses, interactive learning tools, learning management systems, video conferencing, network access, and automated management systems (Wang et. al., 2023). At INU, the practical application of an SC includes features such as free Wi-Fi, the Moodle Learning Management System (LMS), smart classrooms, electronic barriers for vehicle access, gates using facial recognition for student entry, and smart surveillance systems both inside and outside buildings. Additionally, the campus includes smart chairs, large external advertising screens (75 inches), wireless security systems, and queuing systems for organizing lines.

2.Self-Directed Learning (SDL)

This refers to individuals taking an active role in managing their education (Loeng, 2020; Jiang & Fu, 2025). The most widely accepted definition of SDL was proposed by Guglielmino (2008). According to Guglielmino (2008), SDL is a combination of attitudes, values, and skills that increases the likelihood that an individual can engage in SDL effectively. For this study, SDL is examined in terms of the degree of control learners have over their learning process. It is also explored through the skills and abilities necessary for students to succeed in SDL, including creativity, enthusiasm for learning, independence, initiative, self-concept, access to learning opportunities, and a positive outlook on the future. Additionally, SDL is linked to the ability to use fundamental problem-solving and learning skills. The SDL Readiness Scale (SDLRS), derived from Guglielmino (2008), is a self-report survey that incorporates Likert-type items. This tool was adapted, for undergraduate university students utilizing SC, to be utilized to assess students' SDL.

3.Attitudes toward learning (ATL)

The concept of attitude refers to the entrepreneurial mindset, which has been central to both the industrial and informational revolutions. It remains a driving force in successful projects that generate significant human satisfaction for all those involved (Paz et al., 2022). To examine the students' ATL, a survey was used in this study. Originally the survey was developed by Sandman (1973) and it was adapted for undergraduate university students utilizing SC.

Literature Review

This section starts by introducing the concept of SC from multiple perspectives. It then describes the different elements and components that could be included in the educational context of an SC. The review also explores the evolution of SC in higher education, highlighting developments in both developed and developing regions.

Smart Campus (SC)

The concept of a SC in education has garnered significant attention as educational institutions seek to utilize technology to improve learning experiences, streamline administrative processes, and enhance overall efficiency. Numerous studies have explored the implementation and impact of SCs on various facets of education.

A major focus in the literature is the application of smart technologies to enhance students' learning experiences. For instance, smart classrooms that feature interactive displays, digital learning tools, and adaptive technologies have proven effective in fostering student engagement, collaboration, and personalized learning (Huang et al., 2018). Additionally, the use of augmented reality and virtual reality has been investigated for creating immersive and interactive learning environments (Gavish et al., 2020). These studies emphasize the potential of SC technologies to support innovative teaching methods and improve educational outcomes.

Administrative processes in educational institutions have also been improved through SC initiatives. Studies have demonstrated that integrating smart technologies can simplify tasks such as course registration, scheduling, and campus service management (Son et al., 2018). Automated systems powered by artificial intelligence algorithms have been used to optimize resource allocation, boost operational efficiency, and enhance administrative decision-making (Zhang et al., 2020). These findings underscore the potential of smart campuses to improve administrative effectiveness and redirect resources toward supporting student services.

Sustainability and environmental concerns are also key areas of focus in the literature. Smart Campus (SC) technologies allow for the collection and analysis of real-time data on energy consumption, occupancy, and resource use. This data-driven approach helps educational institutions adopt energy-efficient practices, reduce their carbon footprint, and promote sustainable campus operations (Le et. al., 2019). Additionally, SC can support the integration of smart grids, the use of renewable energy, and improved waste management, contributing to more environmentally sustainable campuses.

However, the literature also highlights various challenges and considerations. Privacy concerns regarding the collection and analysis of sensitive data are a significant issue (Jin et. al., 2017). Educational institutions must prioritize data

security, establish strong protocols, and comply with relevant regulations to protect student information. Additionally, the financial implications and return on investment of (SC) technologies must be carefully assessed (Wu et al., 2021). Successful implementation requires thorough planning, proper budget allocation, and continuous support from all stakeholders.
In conclusion, the literature on SC in education highlights the potential advantages of incorporating smart technologies into both learning environments and administrative functions. From enriching the learning experience and fostering student engagement to enhancing administrative efficiency and supporting sustainability efforts, SC provides educational institutions with valuable opportunities to evolve in the digital era and improve various facets of education.

Self-Directed Learning (SDL) and Smart Campus (SC)

Self-directed learning (SDL) has become increasingly important in education, highlighting the role of learner independence and the capacity to take charge of one's learning journey. Smart Campus (SC) technologies provide opportunities to further improve SDL experiences.
The application of smart technologies in educational environments to support SDL has been explored in various studies. Personalized learning systems powered by artificial intelligence algorithms have been developed to tailor information and learning experiences to the individual needs of students (Liu et al., 2019). These platforms offer personalized recommendations, resources, and feedback to enhance SDL.
Self-directed learning (SDL) is significantly supported by SC technologies such as learning analytics and data-driven feedback systems. Learning analytics tools can track and assess students' progress, engagement, and performance to gain insights into their learning preferences and behaviors (Dyckhoff et. al., 2019). This data enables learners to make informed decisions about their learning journey and pinpoint areas where they can improve.
Mobile learning applications and smart devices play a key role in supporting SDL. Mobile apps allow learners to access educational resources anytime and anywhere, encouraging independent learning (Lu et al., 2018). Smart devices, such as smartphones and tablets, provide learners with tools to explore topics of interest, collaborate with peers, and participate in self-paced learning activities.
Additionally, SC technologies promote social learning and collaboration, which are vital aspects of SDL. Online collaborative platforms and social networking tools allow learners to connect with their peers, share knowledge, and engage in collaborative problem-solving (Shih et al., 2019). These technologies create opportunities for students to build communities of practice and participate in meaningful discussions, enriching their SDL experiences.
However, there are challenges in implementing SC technologies for SDL. Some students may struggle to effectively engage with these tools due to the

digital divide and unequal access to technology (Rutherford et al., 2020). Additionally, for students to fully utilize smart technologies for SDL, it is essential to develop their digital literacy skills.

In conclusion, the integration of SC technologies can significantly enhance SDL in education. Personalized learning platforms, learning analytics, mobile apps, and collaborative tools foster learner autonomy, engagement, and ownership of their learning paths. By addressing challenges and ensuring equal access to technology, SDL opportunities can be further expanded.

2.3 Student Attitude toward Learning (ATL)

Student attitudes toward learning (ATL) are essential in the learning process, and the integration of SC technologies in education has the potential to positively impact these attitudes. Numerous studies have examined the connection between SC technologies and student ATL.

Engagement is a key aspect of student attitudes that has been studied. SC technologies offer interactive and immersive learning experiences which can motivate and engage students (Yi et al., 2017).

Additionally, SC technologies create opportunities for active and collaborative learning, encouraging positive attitudes toward teamwork and collaboration. Online platforms and social networking tools allow students to connect with their peers, exchange ideas, and collaborate on projects (Shih et al., 2020). By fostering collaboration, SC technologies can have a positive effect on students' ATL.

Self-efficacy is an important aspect of student ATL. SC technologies that provide personalized feedback and support can enhance students' self-perceptions of their abilities. Lin et al. (2019) suggest that adaptive learning systems and intelligent tutoring systems can assess students' progress, identify areas for improvement, and offer relevant feedback and resources. This individualized assistance can boost students' self-esteem and positively influence their ATL.

Moreover, the use of SC technologies can encourage a positive attitude toward technology. As students interact with different digital tools and platforms, they enhance their technological skills and digital literacy, which are crucial in today’s digital world (Son & Kim, 2018). By enhancing students' competence and confidence in using technology, SC technologies help foster a positive ATL.

Many researchers have investigated the concept of smart campuses within universities, focusing on how these technologically advanced environments influence various factors such as students' academic performance, behavioral patterns, and overall engagement. Notable studies include those by Ahmed et al. (2020), Bin Mustafa (2021), Di Dio et al. (2024), Fortes et al. (2019), Lin and Luo (2021), Mostafa (2023), and Popoola et al. (2018). Each of these investigations highlights important relationships between smart campus features—like integrated learning technologies, enhanced connectivity, and innovative learning spaces—and student outcomes.

However, despite the breadth of research in this area, there remains a significant gap in the literature regarding the effect of smart campuses on students' self-directed learning (SDL) and adaptive teaching and learning (ATL). These concepts are critical as they relate to students' ability to manage their own learning processes and adapt to diverse educational strategies, respectively. Addressing this gap could provide valuable insights into how smart campuses can be designed and utilized to foster deeper learning experiences and improve educational outcomes.

However, it is crucial to address potential challenges and barriers to adopting SC technologies and their effect on student ATL. Factors such as access to technology, the digital divide, and the availability of technological support can influence students' perceptions of these tools (Rosen et al., 2018). To encourage positive attitudes toward SC technologies, it is essential to ensure equitable access to technology and provide the necessary support.

In conclusion, integrating SC technologies can positively impact student ATL. By enhancing engagement, collaboration, self-efficacy, and technological skills, these technologies help create a more favorable learning environment and improve student experiences.

Methodology

Research Method

This study employs a quantitative approach using explanatory research methods to explore the causal relationship between the independent variable (technologies) and the dependent variables (students' self-directed learning and attitudes).

Participants

The study population consisted of all students at INU, Jordan, totaling approximately 6,160 students. INU offers six faculties: Nursing, Educational Sciences, Literature and Art, Law, and Finance and Management, during the second semester of the 2024-2025 academic year. The sample was selected using a Stratified Random Sampling technique, specifically a non-probability purposive sampling method. According to Raosoft, with a 5% margin of error and a 95% confidence level, the final sample size was determined to be 362 students.

Instrument

The researchers utilized the following instruments to carry out the study:

Attitude survey

To assess the attitude toward learning at INU with SC technologies, a survey was employed in this study. Originally, the survey was developed by Sandman (1973). The survey consists of six scales: anxiety toward learning, perception of the instructor, value of learning in society, self-concept in learning, enjoyment of learning, and motivation for learning. The instrument

comprises 23 items, rated on a 5-point Likert-type scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The survey was tested for reliability and validity.
The survey was adapted for undergraduate university students utilizing SC. The reliability analysis revealed a Cronbach's alpha of 0.89 for all items, indicating strong reliability. For validity, 20 students outside the study sample were asked to evaluate the survey for face validity. They were invited to provide feedback on whether any items were unclear or needed revision, but no changes were necessary. To further assess reliability, a pilot study was conducted with 20 students, and the Cronbach alpha coefficients for all scales of the survey ranged from 0.61 to 0.81, exceeding the 0.5 threshold recommended by Nunnally (1967, 1978).

Self-directed learning (SDL) survey

The Self-Directed Learning Readiness Scale (SDLRS) is a self-report survey developed by Dr. Lucy M. Guglielmino in 1977. It consists of 58 Likert-type items designed to assess the various attitudes, skills, and characteristics that contribute to an individual's readiness to manage their learning. The scale demonstrated high internal consistency with a Cronbach’s alpha of 0.90, indicating strong reliability. Additionally, the validity of the survey was reported at 0.51.
The SDLRS consists of 58 items, each rated on a 5-point Likert scale. The scale includes the following options: '1=almost never true of me', '2=usually not true of me', '3=sometimes true of me', '4=usually true of me', and '5=almost always true of me'. The points assigned correspond to the numerical value of each option. The total score on the SDLRS is obtained by summing the scores from all 58 items.
The researchers adapted the SDLRS to suit undergraduate university students in a context. To ensure the validity of the tool, content validity was established by presenting the instrument to a panel of 20 experts in the fields of curriculum and teaching methods from Jordanian universities, as well as supervisors from the Ministry of Education. Their feedback helped verify the scientific and linguistic accuracy of the items and their suitability for the target group in measuring the relevant concepts for the study sample. Based on the feedback, some items were revised, and the final version of the scale consisted of 58 items.
To assess the construct validity, the correlation coefficients of each item with the total score, as well as with the relevant subscales, were calculated using a separate sample of 20 male and female students outside the study group. The correlation coefficients between the 58 items and the total instrument score ranged from 0.36 to 0.69, while those between each item and its respective subscale ranged from 0.51 to 0.83. All correlation coefficients were found to be statistically significant and within acceptable ranges, confirming that no items needed to be removed. Furthermore, the correlation between

the subscales and the overall score, as well as the inter-subscale correlations, were statistically significant and of acceptable magnitude, indicating satisfactory constructs validity.
The reliability of the scale was verified using the test-retest method. The scale was first administered to a group of 20 male and female students outside the study sample, and then re-administered two weeks later. The Pearson correlation coefficient between the two sets of scores was calculated, and the reliability coefficient was also determined using the internal consistency method based on the Cronbach alpha equation. The results showed reliability internal consistency coefficients according to Cronbach alpha, as well as reliability on the retest for both the domains and the overall score. These values were considered appropriate for this study (Auda, 2004).

The criterion for evaluating the surveys
To establish the criterion for evaluating the two survey items, the researchers calculated the class width as follows: They determined the range by subtracting the lowest value in the scale from the highest value (5-1=4). Then, they computed the class width by dividing the range by the highest value on the scale, which is 5 (4/5=0.8).
Accordingly, the categories of the arithmetic mean values were determined based on the Likert scale as follows:

Table 1: Criterion for Evaluating Students' Responses.

The criterion for Evaluating Students' Responses	Categories of Arithmetic Mean Values
Very High	4.21 – 5.00
High	3.41 – 4.20
Moderate	2.61 – 3.40
Low	1.81 – 2.60

Ethical Consideration
Approval for this study was granted by the Research Ethics Committee of INU. Participants were informed about the study’s objectives and were assured that their participation was voluntary. They were also notified that they had the right to withdraw from the study at any time.

Acknowledgment:
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Data analysis
Descriptive statistics were used to calculate mean scores and standard deviations. An ANOVA test was conducted to assess the significance of the differences among the mean scores of each variable. Post-hoc comparisons

were performed using the Scheffé method to identify the statistical significance between the arithmetic means. The data analysis was carried out using SPSS version 21.0 for Windows.

Results

Question one: Does SC enhance students' SDL?

To evaluate the effect of the new Smart Campus (SC) on enhancing students' self-directed learning (SDL) at Irbid National University (INU) from the students' perspectives, the researchers employed a questionnaire for data collection. The gathered data were analyzed using the Statistical Package for the Social Sciences (SPSS), where mean scores and standard deviations were calculated to determine how much the new SC contributes to improving students' learning. The results are summarized in Table 2.

Table 2: Means and Standard Deviations for Assessing the Impact of the New SC on Enhancing Students' SDL at INU from Their Perspectives.

No	Paragraphs	Means	Standard Deviations	Level
1.	The SC helped me develop my continuous learning skills.	4.32	0.97	Very High
2.	The SC enabled me to know what I wanted to learn.	4.20	1.07	High
3.	The SC helped me by providing options to clarify things I found unclear.	2.88	1.35	Medium
4.	The SC helped me find ways and methods to learn the things I love to learn.	4.35	0.98	Very High
5.	The SC enhanced my love for learning.	4.44	0.93	Very High
6.	The SC helped me start new projects.	3.56	1.13	High
7.	The SC provided a role for the teacher in guiding all students, specifically what to do all times.	3.98	1.03	High
8.	The SC allowed me to reflect on who I am in life, where I am, and which direction I am heading, forming an essential part of anyone's education and culture.	4.26	1.05	Very High

9.	The SC helped guide my learning.	3.17	1.29	Medium
10.	The SC offered different methods to access information.	4.10	0.99	High
11.	The SC provided applications that support self-directed learning.	3.90	1.01	High
12.	The SC provided me with capabilities that made it easy to implement plans.	3.44	1.25	Very High
13.	The SC provided resources on how to learn.	4.01	1.11	High
14.	The SC sparked my desire to study.	3.96	1.32	High
15.	The SC played a role in taking responsibility for my learning.	4.14	1.16	High
16.	The SC helped me provide effective ways to learn.	4.20	0.99	High
17.	The SC gave me an abundance of things I love to learn, making me wish the day had more hours.	4.14	1.00	High
18.	The SC gave me the ability and time to find time for learning, even when I was very busy.	4.19	1.01	High
19.	The SC helped me understand what I read.	2.84	1.37	Medium
20.	The SC provided a sense of responsibility for my learning.	3.11	1.38	Medium
21.	The SC gave me a sense of satisfaction with my academic achievement, even when I wasn't fully confident in the subject.	4.01	1.00	High
22.	The SC allowed me remote access to the library, preventing boredom.	3.39	1.34	Medium
23.	The SC enhanced my respect for individuals who love to learn new things.	2.93	1.47	Medium

24.	The SC provided me with multiple ways to learn a specific topic.	3.89	1.22	High
25.	The SC played a role in helping me find connections between what I learned and my long-term goals.	4.09	1.04	High
26.	The SC helped me independently learn everything I needed to know.	4.22	1.00	Very High
27.	The SC sparked a strong desire in me to inquire and seek answers to specific questions.	4.04	0.99	High
28.	The SC increased my desire to research questions that have more than one correct answer.	4.10	0.91	High
29.	The SC increased my curiosity for exploration.	3.39	1.31	Medium
30.	The SC increased my love for continuous learning.	4.03	1.00	High
31.	The SC increased my desire to compare myself with others.	3.57	1.34	High
32.	I have no issues with basic learning skills.	2.98	1.31	Medium
33.	I enjoy trying new things, even if I'm not sure how they will turn out in the end.	4.13	1.01	High
34.	I love being guided by people who know what they are doing, especially when correcting my mistakes.	3.99	1.02	High
35.	The SC helped me think of new ways to do things.	3.38	1.23	Medium
36.	The SC helped me think about the future.	4.05	0.94	High
37.	The SC helped me outperform most people in trying to find the things I need to learn.	4.23	0.93	Very High
38.	The SC helped me view problems as challenges, not	3.92	1.02	High

	obstacles.			
39.	The SC helped me motivate myself to do what I needed to do.	3.95	1.06	High
40.	With the help of the smart campus, I became happy with the ways I solved my problems.	4.03	1.13	High
41.	The SC helped me become a leader in learning groups.	4.25	0.98	Very High
42.	The SC provided a suitable environment for discussing ideas with others.	3.99	1.02	High
43.	The SC instilled in me a love for the challenges of learning situations.	4.17	0.98	High
44.	The SC provided an opportunity to learn new things.	3.13	1.40	Medium
45.	The SC allowed me to learn more exciting new things.	4.24	0.97	Very High
46.	I started enjoying learning.	4.24	1.03	Very High
47.	The SC helped me learn successful learning methods.	4.26	1.05	Very High
48.	The SC helped me learn more about my personal growth.	3.57	1.27	High
49.	I have become more responsible for my duties.	4.24	1.03	Very High
50.	Learning how to learn is important to me.	4.05	1.05	High
51.	No matter how long I live, this will not stop me from learning new things.	4.26	0.99	Very High
52.	The SC provided ways that make me love continuous learning.	4.35	0.92	Very High
53.	Learning is a life tool.	2.90	1.38	Medium
54.	I learn several new things on my own.	4.28	0.99	Very High
55.	Learning has changed many things in my life.	4.10	1.03	High

56.	The SC provided methods to learn effectively both in the classroom and when I was alone.	2.48	1.55	Medium
57.	Learners are leaders.	4.10	1.04	High
Overall score		4.26	1.07	Very High

The findings presented in Table 2 indicate that the study participants rated the overall impact of the new Smart Campus (SC) on enhancing self-directed learning (SDL) among students at INU as "Very High." The mean score was 4.26, with a standard deviation of 1.07. In contrast, the mean scores for individual items ranged from 2.48 to 4.44. This variation suggests that the questionnaire responses varied between "Medium" and "Very High" levels.

These results underscore the significant role of the SC in improving students' SDL. This impact can be attributed to the SC's ability to provide essential educational resources, such as free Wi-Fi, Learning Management Systems (Moodle LMS), and smart classrooms. Additionally, the SC supported student organization through features like comfortable chairs and queue management systems.

Moreover, training sessions were offered to students and faculty members on how to utilize SC resources effectively. Feedback mechanisms were also implemented to ensure continuous improvement. These features played a vital role in enhancing SDL among INU students.

The findings are consistent with previous research, suggesting that SC technologies help students discover effective learning strategies (Ruimin, 2025), promote personal and academic growth, and encourage lifelong learning (Camargo, 2024). Moreover, SC integration has made learning more engaging and enjoyable, increasing student motivation and independence (Gomes, 2025). It has also facilitated access to education, promoted research skills (MRM, 2025), and contributed to academic achievement.

Furthermore, the Student Center (SC) has helped students refine their problem-solving skills and learning techniques (Alam, 2022), establish connections between their education and long-term goals (Silva-da-Nóbrega, 2022), and implement their learning plans more effectively (García, 2025). Additionally, it has provided opportunities for students to explore subjects of personal interest (Alam, 2022) while fostering continuous learning habits (Santiko, 2025).

Question two: Does students' gender and academic achievement level influence their SDL?

This study aims to analyze the impact of gender on students' SDL. The results of the gender descriptive data analysis are presented in Table 3.

Table 3: Means and Standard Deviations of Students' Scores by Gender

Gender Variable	N	Mean	Std. Deviation
Male	173	238.2197	28.63053
Female	189	236.6349	24.98018
Total	362	237.3923	26.76099

According to Table 3, the Self-Directed Learning (SDL) scores by gender show an average of 238.22 ± 28.63 for males and 236.63 ± 24.98 for females. The analysis indicates a difference in the mean SDL scores between the two genders. An ANOVA test was conducted using SPSS 21.0 for Windows to determine the statistical significance of these differences. The results of the ANOVA test are presented in Table 4.

Table 4: ANOVA Test Results for the Effect of Gender on SDL Scores

Effect	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	226.836	1	226.836	.316	.574
Within Groups	258303.463	360	717.510		
Total	258530.298	361			

The ANOVA test results in Table 4 indicate that gender does not significantly affect students' SDL scores. The F-value of 0.316, with a significance level (Sig.) of 0.574, exceeds the conventional threshold of 0.05. This suggests that any observed differences in SDL scores between male and female students are likely due to random variation rather than a systematic effect of gender.

These findings support the notion that SDL skills are not inherently linked to gender but are shaped by broader educational and personal factors. Individual learning strategies, motivation, and the academic environment may play a more substantial role in developing SDL skills than demographic variables such as gender.

Furthermore, this study examines the influence of academic achievement levels (acceptable, good, very good, and excellent) on students. The descriptive analysis of gender-related data is presented in Table 5.

Table 5: Average Scores of Students' Self-Directed Learning Based on Academic Achievement Levels

Academic Achievement Level Variable	N	Mean	Std. Deviation
Acceptable	57	216.1930	14.82088
Good	92	241.8478	26.97900
Very Good	97	242.5361	28.36190
Excellent	116	239.9741	25.01980
Total	362	237.3923	26.76099

In Table 5, we can see students' average Self-Directed Learning (SDL) scores categorized by their academic performance. The scores are as follows: students with an "acceptable" level scored an average of 216.19 with a variation of 14.82, and those with a "good" level scored 241.85 with a variation of 27. In contrast, students rated as "very good" had an average score of 242.56 with a variation of 28. Finally, students who achieved an "excellent" level scored an average of 240 with a variation of 25. The analysis indicates noticeable differences in SDL scores depending on how well students perform academically.
Researchers conducted an ANOVA test using statistical software to understand these differences better. The results are shown in Table 6.

Table 6: Results of ANOVA Test on SDL Scores by Academic Levels

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	30782.505	3	10260.835	16.129	.000
Within Groups	227747.793	358	636.167		
Total	258530.298	361			

The ANOVA test results confirm that the variations in SDL scores across different academic levels are significant ($F = 16.129$, $p < 0.05$). This finding suggests that students who excel academically are usually better at being self-directed in their learning. This supports earlier research indicating that high-achieving students are more inclined to take charge of their knowledge, creating effective study habits.
To explore the differences among the academic achievement categories—"acceptable," "good," "very good," and "excellent"— a further detailed comparison was conducted, and the results can be found in Table 7.

Table 7. Multiple Comparisons (post-hoc ANOVA)

Academic Achievement Level Variable	SDL (J)	Mean Difference (I-J)	Std. Error	Sig.
Acceptable	Good	-25.65484*	4.25155	.000
	Very Good	-26.34310*	4.20942	.000
	Excellent	-23.78116*	4.07983	.000
Good	Acceptable	25.65484*	4.25155	.000
	Very Good	-.68826	3.67060	.998
	Excellent	1.87369	3.52123	.963
Very Good	Acceptable	26.34310*	4.20942	.000
	Good	.68826	3.67060	.998
	Excellent	2.56194	3.47025	.909
Excellent	Acceptable	23.78116*	4.07983	.000
	Good	-1.87369	3.52123	.963
	Very Good	-2.56194	3.47025	.909

*The mean difference is significant at the 0.05 level.

The results indicate that students in the "acceptable" category had noticeably lower SDL scores than those in the "good", "very good" and "excellent" categories ($p<0.05$). Interestingly, students in the "good", "very good" and "excellent" categories did not show significant differences, suggesting that SDL scores level off at higher achievement levels.

These findings imply that self-directed learning might be the key to academic success. Students who take more responsibility for their learning often perform better. They tend to be more motivated, set goals for themselves, manage their time effectively, and utilize resources efficiently, all contributing to better academic results. The significant gap in SDL skills between the "acceptable" and higher-achieving students points to an area where improvements can be made for those performing at lower levels.

One possible reason for this link is that students who excel at SDL proactively seek knowledge, adapt their study methods, and overcome challenges. They use more profound learning techniques, such as critical thinking and problem-solving, rather than memorizing information. This idea aligns with educational theories, including Zimmerman’s (2002) self-regulated learning model, which emphasizes the importance of learning, motivation, and practical strategies for academic success.

On the other hand, students with lower SDL scores may find it hard to study independently and might need extra help developing effective study habits. They may struggle with self-discipline and organization or rely more on their teachers. This suggests a need for targeted support to improve SDL skills among students in the "acceptable" category. Educational institutions could

implement structured programs such as SDL workshops, mentorship opportunities, or guided learning experiences to help these students gain more independence in their learning.
Furthermore, the lack of significant differences in SDL scores among the "good", "excellent" and "excellent" groups indicates that once students reach a certain level of academic achievement, their SDL skills seem to stabilize. This could suggest that, beyond a certain point, improvements in SDL become less noticeable, or factors like interest in the subject, the learning environment, or external support begin to play a more critical role in overall academic performance.

Question three: Does SC improve students' ATL?
To find out if the Smart Campus (SC) helps improve students' Attitude Toward Learning (ATL) at Irbid National University (INU), researchers used a questionnaire to gather information. They analyzed the data using a program called SPSS to figure out the average scores and how much the answers varied. The results can be seen in Table 8.

Table 8: Average Scores and Variability Showing the Impact of SC on Students' ATL at INU

No	Paragraphs	Means	Standard Deviations	Level
1.	The SC generates in me the desire to attend lectures.	4.21	1.00	very high
2.	I enjoy being in the lecture hall because of the smart campus.	4.21	1.00	very high
3.	The SC has allowed me to feel comfortable during lectures.	4.24	1.07	very high
4.	The SC has provided the instructor with the opportunity to organize lectures effectively and systematically to achieve their goals.	4.44	0.93	very high
5.	The SC has allowed the instructor to manage lecture time, which effectively contributes to achieving its objectives.	4.38	0.94	very high
6.	The SC has enabled the instructor to use multiple teaching methods in the lecture.	4.33	1.01	very high

7.	The SC has positively influenced the instructor's teaching style, making the lecture more enjoyable and helping me understand many concepts.	4.35	1.00	very high
8.	The SC has provided a suitable environment for interaction between students and the instructor.	4.30	1.01	very high
9.	The SC has made me feel comfortable when the instructor assigns me tasks in the lecture due to the availability of facilities that allow for easy task execution.	4.18	1.06	high
10.	The SC has introduced a variety of teaching methods, enhancing my positive attitude toward attending lectures.	4.24	1.03	very high
11.	The SC has allowed for a focus on higher-order thinking skills.	4.31	1.03	very high
12.	The SC has contributed to increasing students' academic achievement.	4.38	1.00	very high
13.	The SC has enabled the instructor to use various methods that help students overcome some learning difficulties.	4.25	1.04	very high
14.	I enjoy it when I see that the spirit of participation spreads among all students due to the smart facilities provided by the smart campus.	4.31	1.01	very high
15.	The SC has provided multiple teaching methods, reinforcing the concept of self-learning among students.	4.30	1.00	very high
16.	The SC has enabled real-time feedback during lectures through various advanced	4.25	1.05	very high

	methods.			
17.	The SC has introduced diverse assessment methods in lectures.	4.28	1.01	very high
18.	I enjoy lectures because they present non-traditional learning situations due to the smart technology provided by the smart campus.	4.28	1.01	very high
19.	I am happy to keep up with advancements in the use of electronic technologies provided by the smart campus.	4.22	1.00	very high
20.	The SC has addressed my classmates' weaknesses in computer skills and related technologies.	3.61	1.28	high
21.	The SC has helped improve the instructor's ability to handle computers and related technologies.	3.35	1.48	medium
22.	The SC has made computers available for learning within the university.	3.67	1.33	high
23.	The SC has improved the classroom environment in terms of lighting, ventilation, and other factors.	3.56	1.51	high
Overall score		4.16	0.16	very high

According to Table 8, the majority of students rated the Smart Campus as having a "very high" impact on their learning attitudes, with an average score of 4.16 and a small variability of 0.16. The individual scores ranged from 3.35 to 4.44, which means some aspects were seen as "medium" while most were viewed as "very high". This shows that the Smart Campus significantly helps improve students' attitudes towards learning.

The SC included many security features, like electronic gates for cars, facial recognition for student access, smart surveillance systems both inside and outside buildings, and wireless security measures. These improvements made students feel safer and more comfortable on campus, positively impacting their attitudes and reducing difficulties they faced.

Furthermore, the Smart Campus helped teachers organize classes better, leading to improved learning outcomes and effective use of lecture time. The variety in teaching methods also encouraged better academic performance from students.

A key highlight from the survey results is that the SC improved how instructors teach, making classes more engaging. This, in turn, motivated students to attend more regularly because they enjoyed the classroom atmosphere. The SC encouraged interaction between students and teachers, allowing students to feel more comfortable completing tasks in class, whether alone or in groups.

Moreover, the SC offered a chance to use different teaching methods, which helped students have better feelings about attending classes. It also allowed teachers to try various strategies to tackle some challenges that students encounter. The variety of assessment methods introduced through the SC provides students with enjoyable and new educational experiences using the latest technologies available on campus, students also appreciated being able to keep up with technological advancements at the Smart Campus.

Question four: Does students' gender and academic achievement level influence their attitude toward learning (ATL)?

This study looks into how gender impacts students' Attitudes Toward Learning (ATL). The results related to gender are summarized in Table 9.

Table 9: Average Scores and Variability of Students' ATL by Gender

Gender Variable	N	Mean	Std. Deviation	Std. Error
Male	177	95.9379	22.90151	1.72138
Female	185	94.8432	17.95745	1.32026
Total	362	95.3785	20.50276	1.07760

From Table 9, we see that male students scored an average of 96 with a variation of 22.9, while female students scored an average of 94.84 with a variation of 18. These scores show a small difference between genders. To check if this difference is meaningful, an ANOVA test was done using SPSS software. The results are displayed in Table 10.

Table 10: ANOVA Test Results for Students' ATL by Gender

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	108.381	1	108.381	.257	.612
Within Groups	151642.770	360	421.230		
Total	151751.152	361			

The ANOVA results in Table 10 show that there is no significant difference, with an F-value not exceeding a significance level of 0.05. This means that gender does not significantly affect students' overall Attitudes Toward Learning (ATL).

Attitudes toward learning are usually influenced by personal motivation, past learning experiences, teaching methods, and cultural factors rather than gender alone. One reason for the lack of significant differences in ATL by gender could be that both male and female students share similar learning environments and academic expectations, leading to similar attitudes toward learning.

This study also examines how academic achievement levels, acceptable, good, outstanding, and excellent, affect students' ATL. The findings are shown in Table 11.

Table 11: Average Scores and Variability of Students’ ATL by Academic Achievement Level

Academic Achievement Level Variable	N	Mean	Std. Deviation	Std. Error
Acceptable	73	91.5890	22.92793	2.68351
Good	43	93.3721	17.51465	2.67096
Very Good	134	97.4328	16.88815	1.45891
Excellent	112	96.1607	23.48646	2.21926
Total	362	95.3785	20.50276	1.07760

According to Table 11, the ATL scores based on academic achievement levels are as follows: 91.6 ± 22.93 for the "acceptable" category, 93.37 ± 17.52 for the "good" category, 97.43 ± 16.89 for the "very good" category, and 96.16 ± 23.49 for the "excellent" category. The analysis indicates a difference in the mean ATL scores between the various academic achievement levels. To determine the significance of these differences, an ANOVA test was performed using SPSS 21.0 for Windows. The results of the ANOVA test are presented in Table 12.

Table 12: Results of the ANOVA Test on the Effect of Academic Achievement Level on SDL Scores

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1855.432	3	618.477	1.477	.220
Within Groups	149895.720	358	418.703		
Total	151751.152	361			

The results of the ANOVA test (F=1.477, p=0.220) show that the differences in ATL scores among students with different levels of academic achievement are likely due to random chance, not because of their academic performance. Since the p-value is greater than 0.05, we can say that academic achievement does not significantly affect how students feel about learning.

One reason we might not see a strong connection between academic achievement and Attitudes Toward Learning (ATL) is that students at different achievement levels often experience similar learning conditions, teaching styles, and expectations. In many schools, especially those with a set curriculum, all students get access to the same resources, materials, and classroom experiences. This means their feelings towards learning may not change much, even if their grades are different. When everyone has similar support and resources, their attitudes may remain alike, regardless of how well they perform academically.

Furthermore, ATL is a complicated idea that involves more than just grades. It also involves how motivated students are, how they view learning, and their personal beliefs about education. Students with higher academic achievement may generally be more dedicated to learning. Still, their attitudes are not only based on their grades. Students with lower grades may have a positive attitude toward learning but face challenges like test performance, time management, or outside pressures. On the flip side, students who do well academically may feel stressed or overly perfectionistic, leading them to have a neutral or negative attitude toward learning even if their grades are strong.

Since SC technologies have a positive influence on students' SDL and ATL, it is suggested to improve the existing SC features. This could include adding interactive learning tools, personalized educational experiences, and resources that encourage independent learning. Increasing access to online learning platforms and using digital technologies can help creating a more engaging and supportive learning environment. Future research should look into other factors that affect SDL and ATL, such as cultural influences, teaching methods, and support outside of school. Understanding these factors better will help improve education strategies and learning results, making sure all students benefit from better learning experiences, regardless of their academic performance.

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