Awareness and utilisation of IoT tools for personalised learning among undergraduates at the University of Ibadan, Nigeria

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Abstract. This study examined undergraduates' awareness and utilisation of Internet of Things (IoT) tools for personalised learning across selected faculties at the University of Ibadan, Nigeria. The study employed a descriptive research design incorporating quantitative and qualitative approaches. A structured questionnaire was administered to 317 students, of whom 284 returned usable responses, and the data were analysed using descriptive and inferential statistics. The findings reveal that while awareness of IoT tools is relatively widespread, students' understanding of IoT is largely conceptualised within general digital technology rather than as a network of interconnected, data-driven systems. Students mostly engage with IoT-enabled devices such as smartphones, connected learning platforms, and cloud applications, while advanced IoT systems like wearable sensors and adaptive learning environments are rarely used due to limited exposure and cost. Multivariate analysis showed that motivation, habit and experience, performance expectancy and facilitating conditions each predicted utilisation, whereas awareness was predicted only by habit and experience, performance expectancy and faculty affiliation. However, the self-reported nature of the data suggests possible response bias, as respondents' perceived familiarity may not reflect technical IoT literacy. The study concludes that there is a conceptual gap between awareness of digital tools and understanding of IoT ecosystems that enable machine-to-machine interaction and automated learning feedback.

Keywords: University of Ibadan, Internet of Things (IoT) tools, personalised learning, academic engagement, awareness, utilisation, motivation, institutional support, digital divide, UTAUT-2

1. Introduction

The Internet of Things (IoT) is an emerging technological framework that connects physical and digital devices through the internet, enabling them to collect, exchange, and act on data autonomously. Unlike traditional information and communication technologies (ICTs) that facilitate human-to-computer interactions, IoT systems enable machine-to-machine and device-to-device communication, forming intelligent networks capable of generating real-time insights [48]. IoT comprises embedded sensors, actuators, and cloud-based analytics that support automation, efficiency, and interconnectivity across domains such as education, healthcare, transportation, and finance [31, 47].

In educational settings, IoT represents an evolution beyond digital learning tools. It connects learning devices, smart classrooms, and cloud-based platforms into unified systems that monitor student performance, personalise learning content, and provide adaptive feedback. For instance, wearable devices, RFID-enabled attendance systems, and IoT-integrated learning management systems allow data from multiple sources to be synchronised, thereby supporting continuous and individualised learning experiences [6, 40]. This interconnected environment transforms the role of students from passive recipients of information to active participants in self-directed and data-supported learning.

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Personalised learning, supported by IoT, refers to the tailoring of instruction and content to meet individual learner needs. IoT-enabled systems analyse learner data to adapt tasks, monitor progress, and suggest next steps in real time [9, 38]. Such systems leverage smart sensors, learning analytics, and cloud computing to identify learning gaps and propose targeted interventions [2]. By facilitating automation and connectivity, IoT enhances access, flexibility, and engagement in learning, especially in environments constrained by time, distance, and resources [12, 25].

However, despite increased IoT integration in education, there is limited understanding of the factors influencing students' awareness and use of these technologies, particularly within the framework of the unified theory of acceptance and use of technology 2 (UTAUT-2). Although studies such as those by Nikolopoulou, Gialamas and Lavidas [33] and Faqih and Jaradat [17] have explored related areas using the UTAUT-2 model, their focus has been on teachers' use of mobile internet and on the adoption of augmented reality – not on IoT in personalised learning for students. Existing research has therefore not fully addressed how UTAUT-2 constructs such as performance expectancy, facilitating conditions, hedonic motivation, and habit affect students' interaction with IoT tools for personalised learning. This gap limits the development of effective strategies to promote IoT adoption in education. Without adequate knowledge and use of IoT technologies, undergraduates may miss opportunities for enhanced academic engagement and achievement, since personalised learning through IoT can support diverse learning styles, offer timely feedback, and create flexible, student-centred learning environments.

In the Nigerian context, however, awareness of IoT as a connected ecosystem remains limited. Many students conflate IoT with general ICT applications such as e-learning platforms, mobile apps, and digital games, which are not IoT tools unless integrated within data-sharing networks. This conceptual confusion impedes meaningful IoT adoption for learning innovation. Therefore, it is imperative to investigate students' level of awareness, patterns of utilisation, and motivational factors influencing their engagement with IoT tools for personalised learning. Understanding these dynamics will clarify the extent to which IoT principles – interconnectivity, automation, and data-driven decision-making – are being realised in Nigerian higher education.

The broad objective of this study was to investigate the role of IoT in personalised learning among undergraduates in selected faculties at the University of Ibadan, Nigeria. Specifically, the study aimed:

1. To assess the level of awareness of IoT tools among the undergraduates.
2. To examine the usage patterns and types of IoT tools used for personalised learning.
3. To identify the motivators for choosing IoT tools for personalised learning.
4. To ascertain the perceived usefulness of IoT tools for learning outcomes.
5. To identify the barriers and facilitating conditions affecting the use of IoT tools.

The following null hypotheses, each referring to the awareness and utilisation of IoT tools for personalised learning among undergraduates at the University of Ibadan, were tested at the 0.05 level of significance:

H_{o1}: There is no significant variation in the effect of motivation on awareness and utilisation.

H_{o2}: There is no significant variation in the effect of habit and experience on awareness and utilisation.

H_{o3}: There is no significant variation in the effect of performance expectancy on awareness and utilisation.

H_{o4}: There is no significant variation in the effect of facilitating conditions on awareness and utilisation.

H_{o5}: There is no significant variation in the combined effect of motivation, habit and experience, performance expectancy and facilitating conditions on awareness and utilisation.

2. Theoretical framework and literature review

Two theoretical models were used to guide the study: unified theory of acceptance and use of technology 2 (UTAUT-2) and uses and gratifications theory (UGT).

2.1. Unified theory of acceptance and use of technology 2 (UTAUT-2)

UTAUT-2, developed by Venkatesh, Thong and Xu [45], extends the original UTAUT model to better explain consumer adoption of technology. While the original model focused on organizational settings and included performance expectancy, effort expectancy, social influence, and facilitating conditions moderated by gender, age, experience, and voluntariness, UTAUT-2 adds three new constructs: hedonic motivation, price value, and habit. These additions reflect the broader motivations influencing individual technology use in everyday, non-organizational contexts.

The model proposes that behavioural intention is shaped by both utilitarian and intrinsic motivations, including enjoyment and cost perceptions, while use behaviour is influenced by behavioural intention and facilitating conditions. A validation study with 1,512 mobile internet users found that UTAUT-2 explained 74% of the variance in behavioural intention and 52% in use behaviour, indicating stronger predictive power than the original model. Each construct captures a different dimension of user behaviour. Performance expectancy reflects perceived usefulness; effort expectancy involves ease of use; social influence considers the opinions of significant others; facilitating conditions refer to available resources and support; hedonic motivation captures enjoyment; price value addresses cost-benefit perceptions; and habit represents the automaticity of repeated use.

The effects of these constructs vary based on demographic factors. For instance, men are often more influenced by performance-related aspects, while women may respond more to ease of use, cost, and social input. Age influences sensitivity to different factors, with younger users often more performance-driven and older users valuing simplicity and encouragement. Experience plays a role in forming habits, although habitual behaviour may still vary among users with similar exposure. UTAUT-2 has become a widely applied framework in consumer technology research, including studies on mobile internet use and health technologies, due to its comprehensive and context-sensitive design.

2.2. Uses and gratifications theory (UGT)

The uses and gratifications theory, developed by Katz, Blumler and Gurevitch [26], provides a user-centred explanation of media consumption. It challenges the notion of passive audiences, arguing instead that individuals actively seek media to fulfil various needs. This theory builds on earlier work such as Herzog [21] on daytime serial listeners, emphasising that audiences pursue cognitive, emotional, and escapist gratifications based on their own motivations and circumstances.

UGT posits that people choose specific media based on the perceived ability of the content to meet personal needs. Gratification sought refers to the anticipated satisfaction before using a medium, while gratification obtained is the actual experience, which in turn influences future media choices. Katz, Blumler and Gurevitch [26] categorised audience needs into cognitive (information-seeking), affective (emotional enjoyment), personal integrative (self-esteem and identity), social integrative (connecting with others), and tension-release (relaxation and escape). These categories provide insight into why people use different media in different contexts.

The theory also emphasises the competitive nature of media, where platforms compete to satisfy users' diverse and shifting needs. Media use is thus deliberate, goal-directed, and shaped by psychological and social factors. Over time, UGT has responded to methodological criticisms by incorporating more empirical rigor and aligning with media effects research, and it remains a valuable framework for analysing how and why people engage with technology in a dynamic environment.

The two models are complementary for the present study. UTAUT-2 accounts for the structural determinants of adoption – performance expectancy, facilitating conditions, hedonic motivation, and habit – which govern whether students are positioned to use IoT tools at all. UGT accounts for what students seek from those tools, emphasising their active role in selecting technologies that satisfy specific learning needs such as convenience, interactivity, autonomy, and academic gratification. Read together, they address both the conditions that enable IoT use and the gratifications that motivate it, which is the combination this study examines in the Nigerian higher education context.

2.3. Review of empirical literature

2.3.1. Effectiveness of personalised learning

The evidence that tailoring instruction to individual needs improves engagement and attainment is now reasonably settled, though its magnitude varies with implementation conditions. Reviews of adaptive technologies, differentiated instruction, and project-based learning conclude that such approaches meet diverse learner needs effectively [22], and a systematic review of higher education found that 59% of studies reported improved academic performance and 36% greater engagement, most often through platforms such as McGraw-Hill's LearnSmart and Moodle [16]. The same pattern holds outside Western settings: personalised learning environments produced significant academic gains among Nigerian secondary students, with males benefiting more [37], and tailored instruction succeeded in Saudi universities, but only where resources, collaboration, and clear implementation goals were in place [9]. That conditionality recurs in the delivery literature. Learning management systems and mobile learning improve achievement, motivation, and engagement [13, 14, 19], and structured student feedback amplifies these gains [46], yet outcomes track teacher beliefs and blended-design choices as much as the technology itself [28]. Personalisation, in other words, is an achievement of the surrounding system rather than a property of the tool.

2.3.2. Awareness and adoption of IoT in higher education

Studies of IoT specifically report a consistent gap between exposure and comprehension. Users engage with IoT frequently while understanding it poorly, with security concerns further impeding adoption [18]; awareness is uneven across groups, running higher among men in a Greek sample [39]; and where awareness is high it clusters around visible applications such as smart libraries and mobile apps [8]. Work using the technology acceptance model likewise found students well aware of IoT's educational potential, while recommending qualitative follow-up to establish what that awareness actually consists of [24, 41], and IoT use among students is now widespread enough to indicate genuine integration into higher education [34]. More recent work sharpens the same point. A study of EFL teachers found awareness of IoT concentrated in general connectivity rather than in the data-exchange properties that define it [29], and an African study of Gen Z undergraduates identified usability and infrastructural readiness, rather than familiarity, as the operative constraints on IoT adoption [30]. Evidence from African higher education institutions on a parallel technology shows the same asymmetry between broad awareness and much narrower informed adoption [36].

2.3.3. Determinants of acceptance

Perceived usefulness is the determinant most consistently implicated. It significantly influenced students' adoption of cloud-based platforms in Saudi universities alongside ease of use [10], and it was the key factor linking individual and technological variables in Nigerian mobile learning adoption [35]. Digital literacy and prior awareness operate as preconditions rather than as competing predictors [32]. Applying UTAUT directly, performance expectancy, effort expectancy, and social influence emerged as predictors of institutional IoT use [3], and a recent readiness-based analysis of IoT biometric systems in higher education found that user optimism and innovativeness separated adopters from non-adopters more sharply than access did [42]. The applications these determinants govern are well documented: IoT supports smart classrooms and digital campuses, improving remote learning, resource management, and collaboration [1]; it enables flexible and quantifiable learning whose outcomes nonetheless vary by national context [44]; it sustains interdisciplinary and collaborative STEM work [11]; it has improved Arabic reading and writing and student attitudes [5]; and it extends to remote laboratories and to inclusion for students with disabilities [43].

2.3.4. Barriers

Against this, the barrier literature is strikingly uniform across settings. Privacy, infrastructure, cost, Wi-Fi reliability, scalability, and trust recur as the principal constraints [20, 27], to which device complexity, the absence of standards, and inadequate teacher training are added, even by authors documenting benefits such as attendance automation and parental monitoring [7]. Institutional capacity is implicated as much as student capacity: financial and training deficits among university IT staff limited deployment in Jordan [4]. In Nigeria the constraint set is wider still, extending to fraud, low technical expertise, unsupportive policies, and cyberattacks [23].

2.3.5. The gap addressed by this study

Three limitations follow from this body of work. First, awareness is repeatedly measured as self-reported familiarity, which the same studies show to be a poor proxy for understanding IoT as a network of interconnected, data-exchanging devices. Second, the UTAUT-2 constructs have been applied mainly to teachers, to institutional adopters, or to technologies other than IoT, leaving students' use of IoT for personalised learning largely unexamined. Third, awareness and utilisation are usually treated as a single construct, even though the reviewed evidence suggests they may have different determinants. This study addresses all three by measuring awareness and utilisation as distinct outcomes, testing UTAUT-2 and UGT constructs against each, and doing so in a Nigerian university where the barrier conditions identified above are known to obtain.

2.4. Conceptual framework

The conceptual framework for this study integrates the UTAUT-2 and UGT, focusing on six core constructs: motivation, performance expectancy, facilitating conditions, habit, awareness, and utilisation (figure 1). Motivation is the internal or external drive prompting individuals to pursue goals. In the context of personalised learning, students are driven to use IoT tools to achieve academic objectives and enjoy autonomy. Both UTAUT-2 and UGT highlight the roles of hedonic motivation and user needs in technology adoption.

Performance expectancy refers to the belief that using a technology will enhance academic performance. Students are more likely to engage with IoT tools such as interactive simulations when they perceive them as valuable and effective for learning.

Facilitating conditions refer to the technical, institutional, and infrastructural supports such as internet access, IoT-enabled devices, technical assistance, and supportive policies that promote IoT adoption in personalised learning. Habit reflects the automatic use of technology formed through repetition; consistent use of IoT tools like smart devices makes usage routine and reinforces adoption. Awareness denotes students' understanding of IoT technologies, their benefits, and peer usage, which significantly shapes their intention to adopt them, as noted in UTAUT and UGT. Utilisation is the actual application of IoT tools to improve learning, including interactive classrooms, time management, and adaptive learning. This integrated framework, drawing on UTAUT-2 and UGT, highlights the psychological, environmental, and behavioural factors influencing IoT adoption among undergraduates.

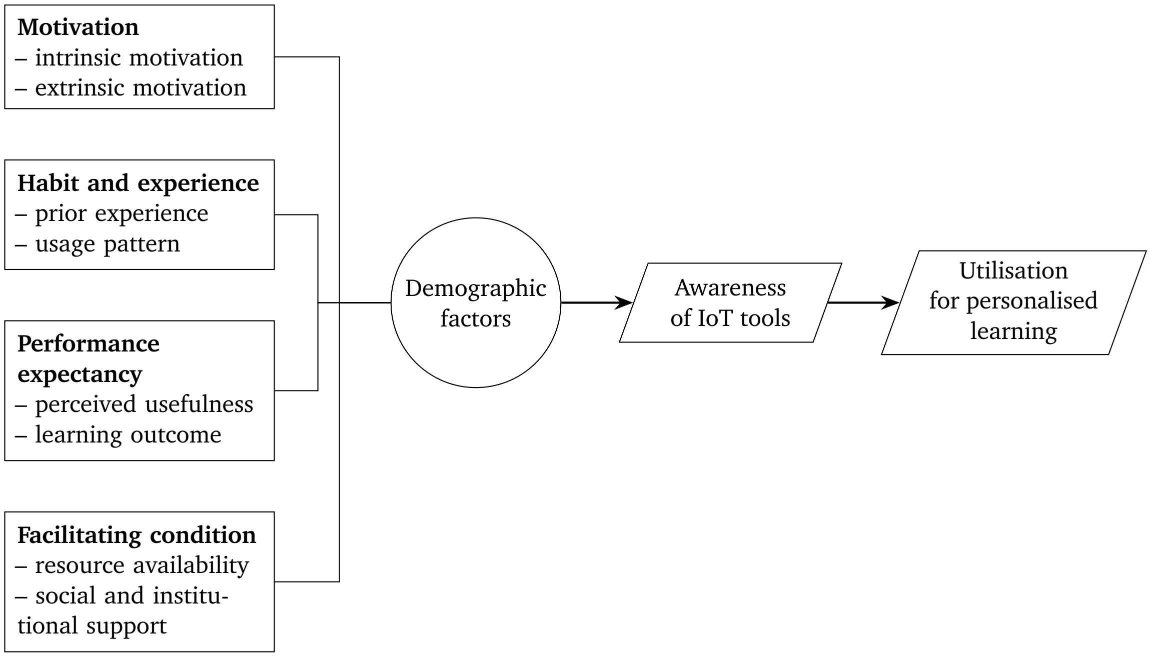

Figure 1: Research conceptual framework.

3. Methodology

3.1. Research design

A descriptive survey design incorporating quantitative and qualitative components was adopted to explore undergraduates' awareness and utilisation of IoT tools for personalised learning. The quantitative component was used to identify prevailing patterns of IoT awareness and use and to test the study's hypotheses; the qualitative component, drawing on elements of narrative inquiry, used open-ended items to provide contextual insight into how students understand and experience IoT technologies.

3.2. Population and sampling

The study population comprised undergraduate students of the University of Ibadan, Nigeria. Participants were drawn from four faculties through a multi-stage procedure: faculties were selected first, departments were selected within them, and students were then approached by convenience at the final stage, as they were available in halls of residence, lecture rooms, and faculty premises during the collection period. In total, 317 questionnaires were distributed and 284 were returned complete and usable, a response rate of 89.6%. Of the returned questionnaires, 39.79% were paper-based and 60.21% were submitted through Google Forms. All analyses reported below are based on the 284 usable responses.

3.3. Instrumentation

Data were collected using a structured questionnaire developed from the theoretical foundations of UTAUT-2 and UGT. To ensure conceptual accuracy, the questionnaire was refined to reflect the core characteristics of IoT – device interconnectivity, data synchronisation, and automated learning support – rather than general ICT usage. Questions on device use, for instance, were framed to determine whether students' tools (e.g. wearables, smartphones, cloud services) interacted across systems to generate personalised feedback or adaptive learning experiences.

The instrument consisted of seven sections, each developed from theoretical foundations, existing studies, and original constructs. Section A gathered demographic data such as age, gender, level, and faculty. Section B assessed awareness of IoT technologies and their educational applications, using yes/no questions, sources of awareness, and Likert-scale ratings of awareness levels. Section C covered habits and experience with IoT, identifying the types of tools used and their frequency of use on a five-point scale. Section D examined motivation, distinguishing intrinsic factors such as personal growth and autonomy from extrinsic drivers such as peer and institutional influence. Section E measured performance expectancy through perceptions of the usefulness and learning outcomes of IoT tools. Section F covered the extent and frequency of IoT use for personalised learning and its perceived benefits. Section G addressed facilitating conditions such as access to resources and institutional support, with space for students to describe challenges and enabling factors in their own words.

3.4. Administration of the instrument

The instrument was administered by the researcher between December 10, 2024 and January 4, 2025. A self-administration approach was adopted in both paper-based and digital (Google Forms) formats. Respondents were approached in their halls of residence, lecture rooms, and faculty premises for the paper-based administration, while the Google Form was shared through the departmental group chats of the sampled departments. This dual strategy was employed to widen coverage, particularly for students studying remotely or off-campus, and the digital mode also suited a study whose respondents were by definition technology users.

3.5. Validity and reliability

Content validity was established by ensuring that items corresponded with accepted IoT definitions emphasising networked communication among devices. Internal consistency was assessed for the ten constructs using Cronbach's α (table 1). Coefficients ranged from 0.649 to 0.923. Eight of the ten constructs fall in the high to excellent range, with perceived usefulness and learning outcome highest at 0.923; only awareness (0.678) and usage pattern (0.649) fall within the moderate range, and results for these two constructs are interpreted accordingly.

Table 1
Internal consistency of the study constructs.

Construct	**Cronbach's α**
Awareness	0.678
Usage pattern	0.649
Intrinsic motivation	0.909
Extrinsic motivation	0.864
Perceived usefulness	0.923
Learning outcome	0.923
Personalised learning resources	0.902
Benefits of utilising IoT for personalised learning	0.832
Resource availability and barriers to IoT utilisation	0.841
Social and institutional support	0.921

Because the data are self-reported, responses may reflect perceived familiarity rather than technical understanding of IoT. This potential response bias was mitigated at the point of administration by clarifying the definition of IoT for respondents, and at the point of analysis by cross-referencing closed responses against the open-ended items.

3.6. Method of data analysis

Quantitative data were analysed in SPSS. Frequency distributions and descriptive statistics were used to summarise the socio-demographic profile, awareness, usage patterns, motivation, perceived usefulness, and barriers. The hypotheses were tested using multivariate analysis of covariance (MANCOVA), with awareness and utilisation as the two dependent variables and age, gender, level, and faculty as covariates. Responses to the open-ended questions were collated and categorised thematically, and representative excerpts are reported alongside the corresponding quantitative results.

4. Results

4.1. Socio-demographic information

Table 2 presents the frequency distribution of the socio-demographic profile of the respondents by gender, age and level of study.

Table 2
Distribution of socio-demographic information.

Variable	Frequency	%
Gender		
Male	124	43.7
Female	160	56.3
Total	284	100
Age		
16–20 years	122	43.0
21–25 years	131	46.1
26–30 years	31	10.9
Total	284	100
Level		
100 level	45	15.8
200 level	58	20.4
300 level	77	27.1
400 level	72	25.4
500 level	24	8.5
600 level	8	2.8
Total	284	100

Of the 284 respondents, 56.3% were female and 43.7% male. Most fell within the 21–25 years (46.1%) and 16–20 years (43.0%) age brackets, with a smaller proportion aged 26–30 years (10.9%); the mean age was 21.4 years. Respondents were spread across academic levels, with the highest representation from 300 level (27.1%), followed by 400 level (25.4%), 200 level (20.4%), 100 level (15.8%), 500 level (8.5%), and 600 level (2.8%).

4.2. Awareness of IoT tools

4.2.1. Prior exposure to IoT

Most respondents, 69.4%, indicated that they were aware of IoT tools, while 30.6% were not.

4.2.2. Sources of awareness

Figure 2 shows the sources through which respondents became aware of IoT tools. Social media was the leading source, accounting for 35.7% of responses, followed by friends and peers (25.3%) and online courses and webinars (20.6%). Lectures were the least frequently cited source, at 18.4%. Awareness therefore arises predominantly outside formal instruction.

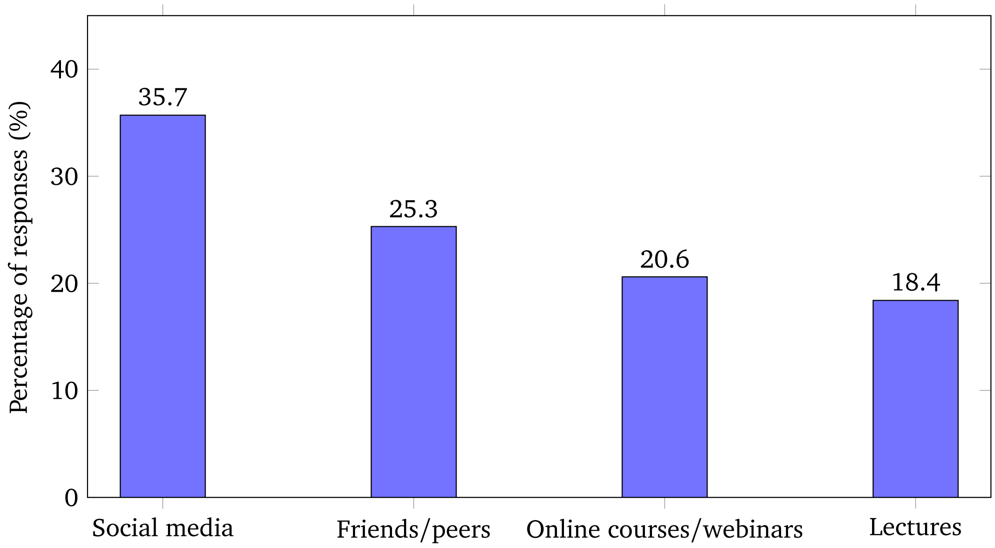

Figure 2: Sources of awareness.

4.2.3. Self-rated level of awareness

Respondents' self-rated awareness of IoT tools for personalised learning was polarised. The largest group, 32.7%, described themselves as extremely aware, while a comparable 29.9% reported no awareness at all. The remainder were distributed across the intermediate levels: 13.7% very aware, 13.4% moderately aware, and 10.2% slightly aware.

4.3. Usage patterns and types of IoT tools

4.3.1. Types of IoT tools used

Respondents reported using a range of IoT-enabled devices for learning, productivity, and communication. Smartphones were the most widely used, cited by all 284 respondents (23.8% of responses), followed by connected learning platforms (249 responses, 20.9%) and e-book readers (243 responses, 20.4%). Cloud-based applications accounted for 196 responses (16.4%) and virtual assistants for 141 (11.8%). Wearables were the least used, with 80 responses (6.7%). The 1,193 responses recorded across 284 respondents correspond to an average of 4.2 IoT tools per respondent, indicating that most students use several tools in combination.

4.3.2. Frequency of use

Table 3 reports how frequently students use each category of IoT-enabled device. Smart devices such as smartphones and tablets dominate academic routines, used very frequently by 82.7% of students. Wearable devices are at the opposite extreme, with 62.3% never using them for academic purposes. IoT-enabled e-books and readers occupy the middle ground, used frequently by 43.7% of students and very frequently by a further 27.8%.

Virtual assistants, like Siri and Google Assistant, are used occasionally by 29.2% of students, although 39.4% never use them. Cloud-based applications such as Google Drive and Dropbox are also

Table 3
Usage pattern.

	Never	Rarely	Occasionally	Frequently	Very frequently	Mean	Std. Dev.
Smart devices (e.g., smartphones and tablets)	1.4	4.2	4.2	7.4	82.7	4.66	0.857
Wearable devices (e.g., fitness trackers, smartwatches)	62.3	3.5	9.5	11.3	13.4	2.10	1.540
IoT enabled E-books and readers	9.2	3.2	16.2	43.7	27.8	3.78	1.160
Virtual assistants (e.g. Siri, Google Assistant)	39.4	2.8	29.2	15.1	13.4	2.60	1.463
Cloud based applications (e.g. Google Drive, Dropbox)	23.9	3.2	19.0	26.1	27.8	3.31	1.509
Connected learning platform (e.g. Google Classroom, Coursera)	6.3	2.1	10.6	33.5	47.5	4.14	1.105

widely used, with 27.8% using them very frequently. Lastly, connected learning platforms like Google Classroom and Coursera are highly utilised, with 47.5% of students using them very frequently and 33.5% using them frequently.

Respondents were also asked, in an open-ended item, how their past experiences with IoT had shaped their current use of it for personalised learning. Three themes recurred: confidence acquired through trial and error, motivation arising from peer recommendation, and the repurposing of devices previously used for entertainment towards time management and study routines.

> *Previously, I struggled to understand IoT technologies, but after learning through trial and error, I now use them confidently for personalised learning.*
>
> *I learned about IoT tools through peers, which motivated me to integrate them into my studies.*
>
> *I previously used IoT devices for entertainment; now, I leverage them to manage personalised study schedules.*
>
> *The convenience of IoT devices encouraged me to adopt them for organising study schedules.*
>
> *IoT tools helped me overcome procrastination by making personalised learning more engaging.*

These accounts indicate that adoption was incremental rather than immediate, and that informal exposure – particularly through peers – rather than instruction was the common entry point.

4.4. Motivators for choosing IoT tools

4.4.1. Intrinsic motivation

Table 4 reports respondents' intrinsic motivations. The strongest was the desire to control one's own learning process, with which 80.6% strongly agreed and only 8.8% disagreed or strongly disagreed. A majority (72.2%) also agreed that they make decisions aligned with their personal values, though fewer strongly agreed (13.7%). For the statement "I am driven to improve and develop new skills", 42.6% agreed and 34.9% strongly agreed.

Extrinsic motivators were endorsed at broadly similar levels, with academic requirements the strongest (85.2% agreeing or strongly agreeing), followed by technological trends (84.5%), institutional initiatives (82.8%), and peer influence (78.9%). Peer influence therefore ranks lowest of the four, though the margin is narrow and all four exceed three-quarters endorsement.

Table 4
Intrinsic and extrinsic motivation.

Intrinsic	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	Mean	Std. Dev.
Desire to have control over my learning process	4.6	4.2	3.5	7.0	80.6	4.55	1.061
Making decisions that align with my personal values	3.9	3.9	6.3	72.2	13.7	3.88	0.832
I am driven to improve and develop new skills, mastering academic tasks and challenges	4.6	3.5	14.4	42.6	34.9	4.00	1.024
Desire to explore, discover, and understand new concepts in my studies	4.2	5.3	11.6	34.9	44.0	4.09	1.069
I want to engage in meaningful activities that contribute to my academic and personal growth	4.9	3.5	10.9	37.3	43.3	4.11	1.058
To feel effective in my academic efforts and to achieve success through personal commitment	4.2	4.9	10.2	34.9	45.8	4.13	1.060
Extrinsic							
Academic requirements	5.3	4.9	4.6	4.2	81.0	4.51	1.129
Peer influence	8.1	6.3	6.7	53.2	25.7	3.82	1.131
Institutional initiatives	3.9	5.3	8.1	34.9	47.9	4.18	1.045
Technological trends	3.2	6.0	6.3	29.6	54.9	4.27	1.033

Asked in an open-ended item which factors motivate their use of IoT tools for personalised learning, respondents pointed chiefly to flexibility of access, real-time progress tracking and feedback, self-paced study, and prompts that support organisation:

> *Access to a wide variety of learning resources.*
>
> *The ease of tracking my academic progress in real time.*
>
> *Learning from anywhere at any time.*
>
> *Learning at my own pace without external pressure.*
>
> *IoT platforms often suggest study schedules based on my activity.*
>
> *Real-time feedback on quizzes and assignments.*
>
> *Collaboration with students worldwide for diverse perspectives and also like minded.*
>
> *Timely notifications about assignments and deadlines.*

The motivations respondents named are predominantly organisational and logistical – access, pacing, scheduling, and deadline management – rather than pedagogical, which is consistent with the pattern of tool use reported in table 3.

4.5. Perceived usefulness and learning outcomes

4.5.1. Perceived usefulness

Table 5 reports respondents' perceptions of the effect of IoT tools on their learning performance and academic progress.

Perceived usefulness was uniformly high. For the statement "IoT tools help improve my learning performance", 78.5% strongly agreed. On enhanced understanding of course material, 67.2% agreed and 16.9% strongly agreed; on learning efficiency, 47.9% agreed and 29.2% strongly agreed. For

Table 5
Perceived usefulness and learning outcomes.

Perceived usefulness	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	Mean	Std. Dev.
IoT tools help improve my learning performance.	4.2	3.5	7.0	6.7	78.5	4.52	1.055
Using IoT tools can enhance my understanding of course material	2.1	5.3	8.5	67.2	16.9	3.92	0.806
I believe that IoT tools help me to learn more efficiently	1.4	4.6	16.9	47.9	29.2	3.99	0.880
The use of IoT tools can make it easier to track my academic progress	2.5	4.2	17.3	30.6	45.4	4.12	1.003
I believe that using IoT tools will lead to higher academic performance	2.8	4.9	15.5	31.0	45.8	4.12	1.026
IoT tools are effective in helping me manage my study time more effectively	2.8	3.9	15.1	35.9	42.3	4.11	0.987
Learning Outcome							
Improved understanding	3.9	4.2	11.3	7.4	73.2	4.42	1.091
Easier access to study materials	1.4	4.9	12.7	53.9	27.2	4.00	0.851
Increased engagement	2.8	3.2	16.9	31.0	46.1	4.14	0.997
Improved problem-solving and critical-thinking skills	2.1	4.6	16.2	25.0	52.1	4.20	1.009
IoT tools enhanced ability to retain and recall information during exams or assessments	2.1	3.5	16.9	26.8	50.7	4.20	0.984
IoT provides digital simulation for all the students regardless of where they reside	2.8	4.2	16.2	34.2	42.6	4.10	1.003

tracking academic progress, 45.4% strongly agreed, and a similar proportion (45.8%) strongly agreed that IoT tools lead to higher academic performance. On study-time management, 42.3% strongly agreed and 35.9% agreed.

4.5.2. Learning outcomes

Table 5 also reports the perceived effect of IoT tools on learning outcomes. Improved understanding drew the strongest endorsement, with 73.2% strongly agreeing that IoT tools aid comprehension. Easier access to study materials was also widely endorsed (53.9% agreeing, 27.2% strongly agreeing), as was increased engagement (46.1% strongly agreeing, 31.0% agreeing). Similarly, 52.1% strongly agreed that IoT improves problem-solving and critical-thinking skills, and 50.7% that IoT tools aid retention and recall during examinations. Digital simulation was valued for equalising opportunity regardless of location, with 42.6% strongly agreeing and 34.2% agreeing.

Asked in an open-ended item how IoT tools help them achieve their learning outcomes, respondents cited real-time feedback, curriculum-aligned materials, repeatable virtual laboratory practice, remote access, and progress tracking on certification platforms:

> *They provide real-time feedback, enabling me to correct mistakes quickly.*
>
> *They offer access to diverse materials that align with my course work.*
>
> *The virtual labs feature on some of the apps I use allow me to practise experiments repeatedly.*
>
> *They facilitate remote learning, eliminating geographical barriers. I can be at home in another state and still learn or connect with my lecturers.*
>
> *They streamline the process of achieving certifications and skill mastery especially apps like Udemy or Coursera or Duolingo is very good with tracking and recommendation.*

The benefits respondents identify are concentrated in feedback speed, material access, and removal of geographical constraint. Notably, the platforms named – Udemy, Coursera, Duolingo, Khan Academy – are content-delivery services rather than networked, sensor-driven IoT systems, a point returned to in Section 5.

4.6. Utilisation of personalised IoT learning resources

4.6.1. Use of IoT tools for personalised learning

Asked whether they use IoT tools for personalised learning, 154 respondents (54.2%) answered yes and 130 (45.8%) answered no.

4.6.2. Frequency of use of specific resources

The results show varying levels of engagement with different IoT-based personalised learning tools among undergraduates. Gamified learning tools, such as Kahoot! and Duolingo, are the most frequently used, with 46.8% always using them and 28.5% often using them, meaning over 75% of students engage with them regularly. Individualised feedback is also widely used, with 43.7% always receiving it and 31.7% often receiving it, showing that students highly value personalised assessment. Similarly, 42.6% always engage with competency-based learning platforms like Coursera and edX, while 32.0% use them often. Digital textbooks with interactive elements, such as Pearson's MyLab, are also well-received, with 45.1% always using them and 26.1% often using them.

Mobile learning apps, like Khan Academy and Quizlet, have 39.1% always using them and 25.4% often using them. Adaptive learning platforms, such as DreamBox and McGraw-Hill's ALEKS, see slightly lower engagement, with 35.6% always using them and 17.6% often using them, while 20.4% never use them. Peer learning networks, like Edmodo and Stack Exchange, are moderately used, with 31.7% always participating and 29.6% often participating, but 11.6% never use them. Online Learning Management Systems (LMS) like Moodle and Blackboard are widely used, with 37.0% using them often and 14.8% always using them, but 17.6% never use them. Learning analytics tools, such as Google Analytics for learning environments, have the lowest engagement, with 21.5% never using them, 18.0% rarely using them, and only 26.1% always using them, meaning that nearly 40% of students have little to no interaction with them.

Asked to explain briefly how they had used the IoT-enabled personalised learning tools they selected, respondents described gamified practice, video tutorials, forum discussion, and notification-driven study prompts:

> *I played educational games on Kahoot!, learning biology concepts while making learning fun.*
>
> *Followed video tutorials on Coursera for data science, gaining insights tailored to their learning needs.*
>
> *Explored peer-reviewed articles and shared insights on Edmodo forums, participating in academic discussions and gaining diverse perspectives.*
>
> *Received individualised study tips through notifications from mobile learning apps like Khan Academy, keeping them focused on their learning goals.*

These uses are largely self-directed and centre on individual practice and scheduling rather than on data exchanged between connected devices.

4.6.3. Overall frequency of utilisation

Most respondents use IoT tools regularly: 41.2% daily and 29.6% weekly, so that over 70% engage with them at least once a week. A further 12.3% use them monthly and 16.9% rarely.

4.6.4. Perceived benefits of utilisation

Respondents rated two benefits in particular. Personalisation of learning was rated a very high benefit by 68.0% and a high benefit by a further 14.8%, giving 82.8% combined endorsement. Improved time management was rated a very high benefit by 33.1% and a high benefit by 51.4%, giving 84.5% combined endorsement. Fewer than 4% saw little or no benefit in either respect.

4.7. Barriers and facilitating conditions affecting the use of IoT tools

Resource availability emerged as a significant constraint on the adoption of IoT tools. A majority (79.6%) strongly agreed that the high cost of IoT devices is a barrier, and inadequate internet access was a further major challenge, with 58.8% agreeing and 26.8% strongly agreeing. Data privacy and security concerns influenced adoption for over 80% of respondents, and 56.3% strongly agreed that the unavailability of smart devices and limited access to learning platforms is limiting. On social and institutional support, lack of peer interest or knowledge was the most frequently endorsed issue (72.9% strongly agreeing), followed by limited collaboration opportunities (82.7% agreeing or strongly agreeing), lack of encouragement from instructors (60.6% strongly agreeing), and lack of institutional support (57.4% strongly agreeing).

Asked in an open-ended item what strategies could raise awareness of IoT tools among undergraduates, respondents proposed campaigns run with student organisations, curricular integration, hands-on training, and industry partnership:

> *Collaborating with student organisations to spread awareness.*
>
> *Creating awareness campaigns during tech fairs and open day.*
>
> *Encouraging faculty to recommend IoT tools during lectures.*
>
> *Collaborating with academic departments to incorporate IoT tools into the curriculum.*
>
> *Providing hands-on training sessions to familiarise students with IoT tools.*
>
> *Partnering with tech companies to organise awareness campaigns.*

4.8. Hypothesis testing

The following hypotheses were tested.

H_{o1}: There is no significant variation in the effect of motivation on the awareness and utilisation

Multivariate analysis of covariance (MANCOVA) is appropriate for this study because it allows for the simultaneous examination of the effect of a single independent variable, motivation, on multiple related dependent variables, namely awareness and utilisation of IoT tools. By including demographic factors such as age, gender, faculty, and level of study as covariates or moderators, MANCOVA controls for their potential confounding influence, thereby isolating the unique contribution of motivation. This technique not only enhances statistical power by accounting for the correlation between the dependent variables but also provides a more nuanced understanding of how motivation influences awareness and utilisation across different student groups. Its application is particularly valuable in educational research where interrelated outcomes and demographic variability are common.

Bartlett's test of sphericity was significant, $\chi^2 = 122.550$, df $= 2$, $p < 0.001$, indicating that the dependent variables are sufficiently intercorrelated for multivariate analysis. The multivariate tests show that faculty has a significant effect (Wilks' $\Lambda = 0.945$, $F(2, 273) = 7.963$, $p < 0.001$, partial $\eta^2 = 0.055$, power $= 0.954$), as does motivation (Wilks' $\Lambda = 0.890$, $F(8, 546) = 4.083$, $p < 0.001$, partial $\eta^2 = 0.056$, power $= 0.993$). Age, gender and level had no significant effect ($p \geq 0.05$).

Table 6 shows the results of test of between subject effects to determine how different independent groups affect the dependent variable. The result indicate that the corrected model is significant

Table 6
H_{o1}: Test of between-subject effect.

Source	Dependent variable	Type III SS	df	MS	F	Sig.	η_p^2	Power
Corrected model	Utilisation	26.414	5	5.283	5.792	.000	.094	.993
	Awareness	46.382	5	9.276	3.527	.004	.060	.915
Intercept	Utilisation	395.749	1	395.749	433.880	.000	.609	1.000
	Awareness	158.948	1	158.948	60.428	.000	.179	1.000
Faculty	Utilisation	1.342	1	1.342	1.471	.226	.005	.227
	Awareness	36.618	1	36.618	13.921	.000	.048	.961
Motivation	Utilisation	24.997	4	6.249	6.851	.000	.090	.994
	Awareness	10.740	4	2.685	1.021	.397	.014	.321
Error	Utilisation	253.569	278	.912				
	Awareness	731.238	278	2.630				
Total	Utilisation	3879.000	284					
	Awareness	3492.000	284					
Corrected total	Utilisation	279.982	283					
	Awareness	777.620	283					

for both utilisation ($F(5, 278) = 5.792$, $p < .001$, $\eta^2 = .094$) and awareness ($F(5, 278) = 3.527$, $p = .004$, $\eta^2 = .060$), indicating that the independent variables explain a meaningful portion of the variance in both cases.

Faculty has a significant impact on awareness ($F = 13.921$, $p < .001$, $\eta^2 = .048$), suggesting that students' faculty of study influences their awareness of IoT tools. However, it does not significantly affect utilisation ($F = 1.471$, $p = .226$). On the other hand, motivation plays a significant role in utilisation ($F = 6.851$, $p < .001$, $\eta^2 = .090$) but does not significantly influence awareness ($F = 1.021$, $p = .397$). All other demographic factors namely age, gender and level have no significant effect as $p \geq 0.05$. The findings indicate that awareness of IoT tools is shaped by faculty differences, while actual utilisation is driven by motivation.

Table 7 presents the result for the parameter estimates of how independent variables influence the dependent variable. The MANCOVA results reveal the influence of motivation and faculty on students' awareness and utilisation of IoT tools. For utilisation, the intercept ($B = 4.027$, $p < .001$) indicates the baseline level for students in the reference motivation category (Motivation = 5). Motivation significantly affects utilisation: students in Motivation category 2 show a strong negative effect ($B = -1.366$, $p < .001$), and category 4 also shows a significant reduction ($B = -0.396$, $p = .002$). Categories 1 and 3 show negative effects, but these are not statistically significant. Faculty does not significantly predict utilisation ($B = -0.061$, $p = .226$).

For awareness, the intercept ($B = 2.205$, $p < .001$) represents the baseline awareness for the reference motivation group. Faculty significantly predicts awareness ($B = 0.317$, $p < .001$), suggesting that the faculty to which students belong contributes positively to their awareness of IoT tools. However, none of the motivation categories significantly predict awareness, with all $p > .05$.

H_{o1} is therefore rejected for utilisation and retained for awareness: motivation drives whether students use IoT tools, while what they know about them tracks faculty affiliation instead.

H_{o2}: There is no significant variation in the effect of habit and experience on the awareness and utilisation

Bartlett's test of sphericity was significant, $\chi^2 = 93.077$, df = 2, $p < 0.001$, indicating that the dependent variables are sufficiently intercorrelated for multivariate analysis. The multivariate tests

Table 7
H_{o1}: Parameter estimates

Dependent variable	Parameter	*B*	SE	*t*	Sig.	95% CI lower	95% CI upper
Utilisation	Intercept	4.027	.168	23.990	.000	3.697	4.358
	Faculty	-.061	.050	-1.213	.226	-.159	.038
	[Motivation=1]	-.767	.446	-1.718	.087	-1.646	.112
	[Motivation=2]	-1.366	.292	-4.680	.000	-1.940	-.791
	[Motivation=3]	-.266	.202	-1.317	.189	-.662	.131
	[Motivation=4]	-.396	.127	-3.124	.002	-.645	-.146
	[Motivation=5]	0	.	.	.	.	.
Awareness	Intercept	2.205	.285	7.735	.000	1.644	2.766
	Faculty	.317	.085	3.731	.000	.150	.484
	[Motivation=1]	.678	.758	.894	.372	-.815	2.170
	[Motivation=2]	-.800	.496	-1.615	.107	-1.776	.175
	[Motivation=3]	.153	.342	.446	.656	-.521	.826
	[Motivation=4]	-.065	.215	-.301	.764	-.488	.359

show a significant effect of habit and experience (Wilks' $\Lambda = 0.886$, $p < 0.001$, partial $\eta^2 = 0.059$, power = 1.000).

Table 8 presents the between-subjects effects. The corrected model is significant for awareness, $F(9,274) = 5.819$, $p < .001$, $\eta^2 = .160$, power = 1.000, but not for utilisation, $F(9,274) = 1.692$, $p = .091$, $\eta^2 = .053$, power = .771.

Habit and experience nonetheless have a significant effect on both dependent variables: awareness, $F(4,274) = 8.550$, $p < .001$, $\eta^2 = .111$, power = .999; and utilisation, $F(4,274) = 2.655$, $p = .033$, $\eta^2 = .037$, power = .737.

Table 9 shows the MANCOVA results which indicates that habit and experience significantly influence both awareness and utilisation of IoT tools for personalised learning. For awareness, the intercept ($B = 3.197$, $p < .001$) represents the baseline level for students with the highest habit and experience level (category 5). Students with lower levels of habit and experience (categories 2, 3, and 4) report significantly lower awareness, with the most substantial decline observed in category 2 ($B = -1.544$, $p < .001$), followed by categories 3 ($B = -1.070$, $p < .001$) and 4 ($B = -0.796$, $p = .002$).

This suggests that students who do not regularly engage with IoT tools, or who have limited prior experience of them, tend to be less aware of them. For utilisation, the intercept ($B = 1.654$, $p < .001$) similarly reflects the level for those in category 5. Students in categories 2, 3, and 4 again exhibit

Table 8
H_{o2}: Test of between-subject effect.

Source	Dependent variable	Type III SS	df	MS	*F*	Sig.	η_p^2	Power
Corrected model	Awareness	124.781	9	13.865	5.819	.000	.160	1.000
	Utilisation	3.711	9	.412	1.692	.091	.053	.771
Intercept	Awareness	34.496	1	34.496	14.478	.000	.050	.967
	Utilisation	17.165	1	17.165	70.426	.000	.204	1.000
Habit and experience	Awareness	81.487	4	20.372	8.550	.000	.111	.999
	Utilisation	2.588	4	.647	2.655	.033	.037	.737
Error	Awareness	652.839	274	2.383				
	Utilisation	66.782	274	.244				

Table 9
H_{o2}: Parameter estimates.

Dependent variable	Parameter	*B*	SE	*t*	Sig.	95% CI lower	95% CI upper
Awareness	Intercept	3.197	.550	5.814	.000	2.114	4.279
	[Habit and experience=2]	-1.544	.324	-4.764	.000	-2.183	-.906
	[Habit and experience=3]	-1.070	.230	-4.651	.000	-1.524	-.617
	[Habit and experience=4]	-.796	.257	-3.099	.002	-1.301	-.290
	[Habit and experience=5]	0	.	.	.	.	.
Utilisation	Intercept	1.654	.176	9.403	.000	1.307	2.000
	[Habit and experience=2]	-.256	.104	-2.465	.014	-.460	-.051
	[Habit and experience=3]	-.207	.074	-2.812	.005	-.352	-.062
	[Habit and experience=4]	-.169	.082	-2.058	.041	-.331	-.007

significantly lower utilisation, with coefficients ranging from −0.256 to −0.169.

H_{o2} is therefore rejected for both dependent variables. Habit and experience is the only construct in the study to predict awareness and utilisation alike, which is consistent with prior exposure being the mechanism through which both develop.

H_{o3}: There is no significant variation in the effect of performance expectancy on the awareness and utilisation

Bartlett's test of sphericity was significant, $\chi^2 = 192.163$, df = 2, $p < 0.001$, confirming significant correlation among the dependent variables and their suitability for multivariate analysis (Wilks' $\Lambda = 0.641$, $F(2, 273) = 76.509$, $p < 0.001$, partial $\eta^2 = 0.359$, power = 1.000).

Table 10 presents the between-subjects effects. The corrected model explains a significant portion of the variance in both awareness ($F(9, 274) = 2.858$, $p = 0.003$, partial $\eta^2 = 0.086$, power = 0.962) and utilisation ($F(9, 274) = 4.917$, $p < 0.001$, partial $\eta^2 = 0.139$, power = 0.999).

Performance expectancy significantly influences both awareness ($F(4, 274) = 5.322$, $p < 0.001$, partial $\eta^2 = 0.072$, power = 0.971) and utilisation ($F(4, 274) = 8.490$, $p < 0.001$, partial $\eta^2 = 0.110$, power = 0.999).

Table 11 shows the result for the parameter estimates. The MANCOVA results reveal that performance expectancy significantly predicts both awareness and utilisation of IoT tools among undergraduates. For awareness, the intercept ($B = 1.539$, $p < .001$) indicates the baseline awareness level for students with the highest performance expectancy (level 5). Students with a performance expectancy of 3 show significantly lower awareness ($B = −0.366$, $p < .001$), suggesting that a reduced belief in

Table 10
H_{o3}: Test of between-subject effect.

Source	Dependent variable	Type III SS	df	MS	*F*	Sig.	η_p^2	Power
Corrected model	Awareness	5.180	9	.576	2.858	.003	.086	.962
	Utilisation	38.934	9	4.326	4.917	.000	.139	.999
Intercept	Awareness	18.067	1	18.067	89.734	.000	.247	1.000
	Utilisation	111.968	1	111.968	127.274	.000	.317	1.000
Performance expectancy	Awareness	4.286	4	1.072	5.322	.000	.072	.971
	Utilisation	29.877	4	7.469	8.490	.000	.110	.999
Error	Awareness	55.169	274	.201				
	Utilisation	241.049	274	.880				

Table 11
H_{o3}: Parameter estimates.

Dependent variable	Parameter	*B*	SE	*t*	Sig.	95% CI lower	95% CI upper
Awareness	Intercept	1.539	.158	9.754	.000	1.229	1.850
	[Performance expectancy=3]	-.366	.088	-4.147	.000	-.540	-.192
	[Performance expectancy=5]	0	.	.	.	.	.
Utilisation	Intercept	4.385	.330	13.292	.000	3.736	5.035
	[Performance expectancy=1]	-1.225	.487	-2.514	.013	-2.184	-.266
	[Performance expectancy=2]	-1.665	.325	-5.127	.000	-2.304	-1.025
	[Performance expectancy=3]	-.509	.184	-2.762	.006	-.873	-.146
	[Performance expectancy=4]	-.336	.128	-2.627	.009	-.588	-.084
	[Performance expectancy=5]	0	.	.	.	.	.

the usefulness of IoT corresponds with lower awareness.

For utilisation, the intercept ($B = 4.385$, $p < .001$) reflects the average utilisation level for students with the highest performance expectancy. Students at every lower level (1 to 4) show significantly reduced utilisation, the greatest reduction being at level 2 ($B = -1.665$, $p < .001$).

H_{o3} is therefore rejected for both dependent variables. Performance expectancy is the strongest single determinant in the study, and the one construct that operates on awareness and utilisation simultaneously through a belief about benefit rather than through exposure.

H_{o4}: There is no significant variation in the effect of facilitating conditions on the awareness and utilisation

Bartlett's test of sphericity was significant, $\chi^2 = 179.822$, df $= 2$, $p < 0.001$, confirming significant correlation among the dependent variables. The multivariate tests show a significant effect of facilitating conditions (Wilks' $\Lambda = 0.897$, $F = 3.745$, $p < 0.001$, partial $\eta^2 = 0.053$), a moderate effect size, with high observed power.

Table 12 presents the between-subjects effects. The corrected model is not significant for awareness, $F(9,274) = 0.839$, $p = .581$, partial $\eta^2 = 0.027$, but is significant for utilisation, $F(9,274) = 4.347$, $p < .001$, partial $\eta^2 = 0.125$, with high observed power (0.998).

Table 12
H_{o4}: Test of between-subject effect.

Source	Dependent variable	Type III SS	df	MS	*F*	Sig.	η_p^2	Power
Corrected model	Awareness	1.619	9	.180	.839	.581	.027	.416
	Utilisation	34.980	9	3.887	4.347	.000	.125	.998
Intercept	Awareness	18.908	1	18.908	88.216	.000	.244	1.000
	Utilisation	104.817	1	104.817	117.223	.000	.300	1.000
Facilitating condition	Awareness	.726	4	.181	.847	.496	.012	.269
	Utilisation	25.923	4	6.481	7.248	.000	.096	.996
Error	Awareness	58.729	274	.214				
	Utilisation	245.002	274	.894				

Facilitating conditions have no significant effect on awareness ($F(4,274) = 0.847$, $p = .496$, partial $\eta^2 = 0.012$, observed power $= 0.269$) but a strong and highly significant effect on utilisation ($F(4,274) = 7.248$, $p < .001$, partial $\eta^2 = 0.096$, observed power $= 0.996$).

Table 13 presents the parameter estimates. For awareness, the intercept ($B = 2.433$, $p < .001$) reflects the baseline level among students in the reference category (facilitating condition = 5). Only category 3 differs significantly from that reference ($B = -1.072$, $p = .001$); categories 1, 2 and 4 show negative coefficients whose confidence intervals include zero and which are not significant. This isolated result should not be read as evidence of an effect on awareness, given the non-significant omnibus test above.

Table 13
H_{o4}: Parameter estimates.

Dependent variable	Parameter	*B*	SE	*t*	Sig.	95% CI lower	95% CI upper
Awareness	Intercept	2.433	.551	4.414	.000	1.348	3.518
	[Facilitating condition=1]	-.817	.741	-1.102	.271	-2.276	.643
	[Facilitating condition=2]	-.255	.472	-.540	.590	-1.184	.675
	[Facilitating condition=3]	-1.072	.324	-3.310	.001	-1.710	-.435
	[Facilitating condition=4]	-.342	.213	-1.605	.110	-.762	.077
	[Facilitating condition=5]	0	.	.	.	.	.
Utilisation	Intercept	4.144	.325	12.739	.000	3.503	4.784
	[Facilitating condition=1]	-1.769	.437	-4.043	.000	-2.630	-.907
	[Facilitating condition=2]	-.412	.279	-1.480	.140	-.960	.136
	[Facilitating condition=3]	-.730	.191	-3.820	.000	-1.107	-.354
	[Facilitating condition=4]	-.210	.126	-1.668	.097	-.457	.038

For utilisation, the intercept ($B = 4.144$, $p < .001$) reflects high baseline utilisation among students with the most favourable facilitating conditions (category 5). Category 1 has a strong significant negative effect ($B = -1.769$, $p < .001$), indicating a marked decline where conditions are least supportive, and category 3 is likewise significant ($B = -0.730$, $p < .001$). Categories 2 and 4 show negative coefficients that do not reach significance.

H_{o4} is therefore rejected for utilisation and retained for awareness. Infrastructural and institutional support governs whether students can act on an interest in IoT tools, but it does not determine whether they come to know about them in the first place.

H_{o5}: There is no significant variation in the effect of motivation, habit, experience, performance expectancy and facilitating conditions on the awareness and utilisation

Bartlett's test of sphericity was significant, $\chi^2 = 82.635$, df = 2, $p < 0.001$, indicating that the dependent variables are sufficiently intercorrelated for multivariate analysis. Using Wilks' Λ, habit and experience had a significant effect, $\Lambda = 0.917$, $F(8,374) = 2.072$, $p = 0.038$, with a small effect size (partial $\eta^2 = 0.042$). Performance expectancy alone was of marginal significance, $\Lambda = 0.923$, $F(8,374) = 1.910$, $p = 0.057$. Its interaction with habit and experience and with facilitating conditions was significant, $\Lambda = 0.866$, $F(12,374) = 2.315$, $p = 0.007$, with a moderate effect size (partial $\eta^2 = 0.069$). The individual constructs therefore have modest effects, while their interaction carries more of the explanatory weight.

Table 14 presents the between-subjects effects. The corrected model significantly influenced both utilisation ($F(95,188) = 2.550$, $p < 0.001$, $\eta^2 = 0.563$) and awareness ($F(95,188) = 1.691$, $p = 0.001$, $\eta^2 = 0.461$). Habit and experience significantly affected utilisation ($F(4,188) = 2.862$, $p = 0.025$, $\eta^2 = 0.057$), as did facilitating conditions ($F(4,188) = 2.581$, $p = 0.039$, $\eta^2 = 0.052$), and the three-way interaction with performance expectancy was also significant for utilisation ($F(6,188) = 3.996$, $p = 0.001$, $\eta^2 = 0.113$). For awareness, by contrast, the same interaction was not significant ($F(6,188) = 0.509$, $p = 0.801$, $\eta^2 = 0.016$).

Table 15 presents the parameter estimates for the interaction effects, showing how combinations of habit and experience, performance expectancy, motivation, and facilitating conditions jointly relate

Table 14
H_{o5}: Test of between-subject effect.

Source	Dependent variable	Type III SS	df	MS	*F*	Sig.	η_p^2	Power
Corrected model	Utilisation	157.633	95	1.659	2.550	.000	.563	1.000
	Awareness	358.324	95	3.772	1.691	.001	.461	1.000
Intercept	Utilisation	253.919	1	253.919	390.170	.000	.675	1.000
	Awareness	73.042	1	73.042	32.750	.000	.148	1.000
Habit and experience	Utilisation	7.451	4	1.863	2.862	.025	.057	.769
Facilitating condition	Utilisation	6.719	4	1.680	2.581	.039	.052	.719
Habit and experience × Facilitating condition × Performance expectancy	Utilisation	15.603	6	2.601	3.996	.001	.113	.970
	Awareness	6.811	6	1.135	.509	.801	.016	.203

to awareness and utilisation. For awareness, students with lower levels of habit and experience (category 2) show reduced awareness ($B = -1.933$, $p = .028$), an effect offset where performance expectancy is at level 3 ($B = 3.933$, $p = .029$). Because the omnibus interaction test for awareness was not significant, these two coefficients are best read as descriptive rather than as established moderation.

In terms of utilisation, the intercept ($B = 4.267$, $p < .001$) again reflects a robust baseline. However, utilisation sharply decreases with certain interaction combinations. The strongest negative effect is observed in students who scored lowest on both motivation and habit/experience ($B = -7.955$, $p = .004$), showing how disinterest coupled with inexperience severely impairs usage. Other significant negative interactions include motivation level 3 with performance expectancy level 2 ($B = -6.067$, $p = .022$), motivation level 2 with facilitating condition level 1 ($B = -4.967$, $p = .027$), and habit and experience level 3 with facilitating condition level 3 ($B = -5.947$, $p = .003$).

The three-way interactions run in both directions. Motivation level 4 combined with habit and experience level 4 and performance expectancy level 3 reduces utilisation ($B = -3.605$, $p = .046$), whereas students at habit and experience level 3 with high performance expectancy and strong facilitating conditions report increased utilisation ($B = 2.233$, $p = .035$). H_{o5} is therefore rejected for utilisation and retained for awareness: the combined model accounts for utilisation through the interplay of psychological readiness, behavioural pattern, and environmental support, but adds nothing to the explanation of awareness.

Table 16 summarises the decisions across the five hypotheses.

Read across the five tests, the pattern is consistent: every construct examined predicts utilisation, whereas awareness is predicted only by habit and experience, by performance expectancy, and by faculty affiliation. Awareness and utilisation are therefore not two measures of one underlying disposition but distinct outcomes with partly different determinants.

5. Discussion of findings

The socio-demographic profile of the respondents offers crucial context for interpreting their engagement with IoT tools for personalised learning. The predominance of young students, largely within the typical undergraduate age bracket in Nigeria, suggests a population well-positioned to interact with digital technologies. Their stage of academic progression also indicates a readiness to explore more complex tools as they advance in their studies. Notably, the considerable representation of female students may reflect broader enrolment trends and opens up avenues for exploring gender-based nuances in technology adoption and use [39].

Across the student body, awareness of IoT tools is relatively widespread but not uniformly deep.

Table 15
H_{o5}: Parameter estimates (interaction effects).

Dependent variable	Parameter	*B*	SE	*t*	Sig.	95% CI lower	95% CI upper
Awareness	Intercept	3.933	0.402	9.792	.000	3.141	4.726
	[Habit and experience=2]	-1.933	0.875	-2.208	0.028	-3.66	-0.206
	[Habit and experience=2] × [Performance expectancy=3]	3.933	1.785	2.203	0.029	0.412	7.455
Utilisation	Intercept	4.267	0.209	20.443	.000	3.855	4.678
	[Motivation=1] × [Habit and experience=1]	-7.955	2.733	-2.911	0.004	-13.345	-2.564
	[Motivation=3] × [Performance expectancy=2]	-6.067	2.618	-2.318	0.022	-11.23	-0.903
	[Motivation=2] × [Facilitating condition=1]	-4.967	2.232	-2.225	0.027	-9.37	-0.564
	[Habit and experience=2] × [Performance expectancy=4]	-1.571	0.832	-1.889	0.060	-3.213	0.07
	[Habit and experience=3] × [Facilitating condition=3]	-5.947	1.974	-3.013	0.003	-9.84	-2.054
	[Habit and experience=3] × [Facilitating condition=4]	-1.483	0.749	-1.981	0.049	-2.961	-0.006
	[Habit and experience=4] × [Facilitating condition=2]	-2.450	1.612	-1.520	0.130	-5.629	0.729
	[Performance expectancy=4] × [Facilitating condition=3]	2.909	1.097	2.652	0.009	0.746	5.073
	[Motivation=4] × [Habit and experience=4] × [Performance expectancy=3]	-3.605	1.797	-2.006	0.046	-7.15	-0.06
	[Motivation=4] × [Habit and experience=3] × [Facilitating condition=3]	3.376	1.630	2.070	0.040	0.159	6.592
	[Habit and experience=2] × [Performance expectancy=4] × [Facilitating condition=3]	-3.909	1.651	-2.367	0.019	-7.167	-0.651
	[Habit and experience=2] × [Performance expectancy=4] × [Facilitating condition=4]	3.155	1.200	2.628	0.009	0.787	5.523
	[Habit and experience=3] × [Performance expectancy=4] × [Facilitating condition=4]	2.233	1.051	2.124	0.035	0.159	4.307

Most of it stems from informal channels – social media and peer interaction – rather than from structured academic instruction, which points to a gap in the formal integration of IoT content into university curricula [8, 34]. That lectures and coursework rank last among sources of awareness is the clearest single indication that IoT literacy is currently being acquired despite the curriculum rather than through it. The tools students prefer follow the same logic. Smartphones are central to their routines because they are accessible and already owned; platforms supporting content access, collaboration, and flexibility follow. Wearables and virtual assistants remain marginal, plausibly

Table 16
Summary of hypothesis tests.

	Construct	Awareness	Utilisation	Decision
H_{o1}	Motivation	$p = .397$	$p < .001$	rejected for utilisation; retained for awareness
H_{o2}	Habit and experience	$p < .001$	$p = .033$	rejected for both
H_{o3}	Performance expectancy	$p < .001$	$p < .001$	rejected for both
H_{o4}	Facilitating conditions	$p = .496$	$p < .001$	rejected for utilisation; retained for awareness
H_{o5}	Combined interaction	$p = .801$	$p < .001$	rejected for utilisation; retained for awareness

because of limited exposure, cost, or unclear academic value [27], which is consistent with utility and ease of use being the operative drivers of technology choice [10].

This distribution matters for how the study's central finding should be read. The tools students actually use – smartphones, cloud storage, learning platforms, and content services such as Coursera and Duolingo – are largely networked content-delivery applications rather than systems in which devices exchange data and act on it automatically. Students' self-reported awareness of "IoT" therefore appears to denote general digital connectivity rather than the machine-to-machine architecture that defines the concept. The same conflation has been reported for EFL teachers, whose awareness of IoT centred on connectivity rather than on data exchange [29], and among African undergraduates, where broad familiarity with a technology coexisted with much narrower informed adoption [36].

Motivations for adoption are both internal and external. Students are driven by a desire for autonomy and personal development and gravitate towards tools supporting independent learning and skill acquisition, consistent with accounts in which personal relevance and self-efficacy shape technology adoption [15, 45]. Extrinsic pressures – academic demands, institutional expectations, and technological trends – shape usage patterns alongside these, with peer influence the least endorsed of the four extrinsic motivators though still endorsed by more than three-quarters of respondents [24]. Perceptions of benefit are uniformly positive: IoT tools are seen as improving performance, engagement, collaboration, and access to materials, which accords with earlier evidence on the potential of IoT to personalise learning [16].

Barriers qualify all of this. High costs, limited access to smart devices, unreliable connectivity, and data privacy concerns constrain how far students can exploit these tools, and the persistence of access problems marks a digital divide within the institution itself [4, 23, 27]. Comparable readiness and infrastructure constraints have been reported for undergraduates elsewhere in Africa [30].

The hypothesis tests sharpen the picture by separating the two outcomes. Motivation strongly predicts utilisation but not awareness, so willingness to engage does not by itself produce exposure [45]. Faculty affiliation predicts awareness but not utilisation, so knowing about IoT does not translate into using it. Habit and experience and performance expectancy predict both, which suggests that prior exposure and a belief in academic benefit are the two mechanisms that operate on knowledge and behaviour alike [2, 10, 14]; user readiness has likewise been found to separate adopters from non-adopters of IoT systems in higher education more sharply than access does [42]. Facilitating conditions, notably, predict utilisation but not awareness: infrastructure and institutional support determine whether students can act on an interest in IoT, not whether they acquire that interest [18]. Because awareness in this sample arrives largely through informal channels that are indifferent to institutional provision, this asymmetry is what one would expect – and it implies that infrastructure investment alone will not close the awareness gap.

Taken together, the findings describe a student population receptive to IoT-enhanced learning but constrained on two distinct fronts: a conceptual gap that curricular integration would address, and an infrastructural gap that investment would address. The two require different interventions, and the evidence here suggests that neither substitutes for the other.

6. Limitations

Four limitations qualify these findings. First, the study was confined to four faculties at the University of Ibadan, which limits generalisability across academic disciplines. Second, convenience sampling at the final stage of participant selection may have introduced bias, since the sample may not fully represent the student population. Third, the data are self-reported, so respondents may have overestimated their awareness or utilisation of IoT tools; this is a particular concern for the awareness measure, given the conceptual conflation discussed above, and awareness and usage pattern were also the two constructs with the lowest internal consistency (table 1). Fourth, the qualitative component was limited to short open-ended responses, which constrained deeper exploration of the contextual dimensions of IoT use. A study combining objective measures of IoT literacy with interview data would address the first and third of these directly.

7. Conclusion

Undergraduate students at the University of Ibadan possess a moderately high level of awareness of IoT tools, but that awareness is largely informal, originating in social media and peer interaction rather than structured academic exposure, and it is skewed towards familiar technologies such as smartphones and learning platforms. Engagement with wearables, virtual assistants, and adaptive systems remains minimal. What students identify as IoT is in most cases general digital connectivity rather than networked, data-exchanging systems, and this conceptual gap is the study's principal finding.

Utilisation is nonetheless substantial: over 70% of respondents use these tools at least weekly, favouring platforms that support flexibility, time management, collaboration, and real-time feedback. The desire for autonomy, skill mastery, and academic success is the dominant driver, with academic requirements, technological trends, institutional initiatives, and peer influence all contributing.

The multivariate analyses show that awareness and utilisation have partly different determinants. Motivation, habit and experience, performance expectancy, and facilitating conditions each predict utilisation. Awareness, by contrast, is predicted only by habit and experience, performance expectancy, and faculty affiliation – neither motivation nor facilitating conditions bear on it. Prior exposure and perceived academic benefit are thus the only mechanisms operating on both outcomes.

Critical barriers remain: high device costs, inadequate connectivity, data privacy concerns, and limited institutional and instructor support. These constraints perpetuate disparities in access, particularly among students with fewer resources, and they bear on utilisation rather than on awareness – which is why addressing them, though necessary, will not on its own resolve the conceptual gap identified above.

8. Recommendations

Because awareness and utilisation proved to have different determinants, they call for different interventions.

To address the conceptual gap, IoT content should be integrated into academic curricula across faculties, so that exposure no longer depends on social media and peer networks. Lecturers can embed IoT tools in assignments, laboratory sessions, and assessments, with curriculum development committees working alongside IT departments on compatibility and accessibility. Targeted workshops and peer-to-peer mentoring should build hands-on experience, including guidance on data security and device functionality, and partnership with technology companies would extend the range of systems students can encounter. Since faculty affiliation predicted awareness, faculties where awareness is lowest are the natural starting point.

To address the infrastructural gap, the university administration should invest in reliable internet provision and subsidise access to IoT devices and learning platforms. Digital learning hubs equipped with networked devices, together with grants or leasing schemes, would give students from underserved backgrounds access to the classes of tool – wearables, sensors, adaptive systems – that cost currently places out of reach. Awareness initiatives such as tech fairs and partnerships with student organisations should be sustained, and instructors and academic advisors should recommend IoT tools and incorporate them into coursework.

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Conflicts of interest

The authors declare that they have no financial or personal relationships that could be perceived as a conflict of interest.

Data availability statement

The datasets generated during and/or analysed during the current study are not publicly available but are available from the corresponding author on reasonable request.

Ethics approval

Ethical approval was not required for this study. Informed consent was obtained from all individual participants included in the study. All participants provided their consent to participate in this study.

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