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Published in:
Journal of Responsible Technology

DOI:
10.1016/j.jrt.2026.100189

Publication date:
2026

Document Version
Publisher's PDF, also known as Version of record

Link to publication in ResearchOnline

Citation for published version (Harvard):
Grant, K, Edgar, DA & Doran, D 2026, 'Addicted to IT: perspectives from educational users – unintended consequences?', *Journal of Responsible Technology*, vol. 28, 100189. https://doi.org/10.1016/j.jrt.2026.100189

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Download date: 27. Nov. 2026

Journal of Responsible Technology 28 (2026) 100189

Contents lists available at ScienceDirect

Journal of Responsible Technology

journal homepage: www.sciencedirect.com/journal/journal-of-responsible-technology

Research Article

Addicted to IT: Perspectives from educational users – unintended consequences?

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ARTICLE INFO

Keywords:
Technology acceptance model (TAM)
Digital dependency
Higher education
Responsible technology
Platformisation
Student wellbeing

ABSTRACT

This paper examines the unintended consequences of accelerated digitalisation in higher education after COVID-19 but before the rapid expansion of generative AI. We extend the Technology Acceptance Model (TAM) to investigate whether university students show indicators of problematic technology use or digital dependency, and whether their responses differ between mandatory institutional systems and voluntary personal technologies. Survey data were analysed using principal component analysis and structural equation modelling. Students reported stronger emotional attachment to, and more frequent engagement with, personal technologies, particularly smartphones, than with institutional systems such as virtual learning environments and university email. Although the data contained behavioural indicators of dependency, the SEM path from influence factors to behaviour was not statistically significant ($p = .510$). We treat this result as a theoretical contribution: persuasive or ostensibly addictive design features do not, by themselves, determine behaviour.

Introduction

Digital transformation is now an established feature of higher education (Mospan & Grinchenko, 2023). Evidence from the post-pandemic period suggests that digitally enabled learning can improve flexibility and access, but may also intensify digital fatigue (Ahmad, 2023), cognitive overload (Kezar, 2014) and burnout. Recent studies (Saleem et al., 2024; Savaş et al., 2025) indicate that fatigue may mediate the relationship between persistent digital obligations and adverse academic outcomes, including reduced attention, emotional exhaustion, procrastination and lower perceived learning quality. This matters because online learning environments have become a routine part of student life. Universities therefore need to look beyond the assumed benefits of digital engagement and consider whether persistent connectivity may also signal over-adoption and over-digitalisation.

The pandemic accelerated existing trends towards platformisation (Fernandez, 2023) and remote delivery, reinforcing a sense of being permanently 'on' and working in 'fast time' (Eriksen, 2001). However, institutional discussions still tend to present educational technology as inherently progressive. Success is commonly measured through adoption, retention, engagement, scalability and operational efficiency, measures that can leave less visible harms out of view.

The findings should be read as a pre-generative-AI baseline. That boundary is important rather than limiting: it gives later studies a point of comparison as AI becomes more deeply embedded in educational practice.

Responsible evaluation needs to ask more than whether a system is effective or efficient. It must also consider whether the system is proportionate, humane and consistent with student well-being. We approach this question by viewing students both as users of institutional systems and as consumers within wider digital ecosystems. We also distinguish between functional and emotional dependency. Functional dependency arises when institutional or personal systems are required for participation and progression. Emotional dependency involves attachment to technologies that support identity, reassurance, belonging and habitual connection. This distinction helps to explain post-pandemic patterns of student technology use.

The study addresses two research questions:

1. Are there signs of problematic technology use or digital dependency among higher education students?
2. Do students respond differently to mandatory institutional systems and to voluntary personal technologies?

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https://doi.org/10.1016/j.jrt.2026.100189

Available online 4 September 2026
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We extend the Technology Acceptance Model (TAM) by adding a construct that captures the potential for technology use to become problematic or dependency-forming. Our concern is not simply whether technology enables learning, but whether educational users experience aspects of its use as addictive.

More specifically, we examine whether educational users display or recognise patterns of over-adoption and digital dependency, even when the technologies concerned also provide clear benefits.

The paper first reviews theories of addiction and technology. It then explains the research design, testing strategy and sample, before presenting the results and discussing digital dependence. The final sections consider the implications for higher education in Scotland and identify priorities for future research.

Taken together, the findings suggest a possible tipping point and provide the basis for a discussion of responsible technology grounded in innovation probity.

Theories of addiction and technology

Addiction research has traditionally focused on substances such as tobacco, alcohol and drugs, as well as behaviours including work and violence (McLellan, 2002). In the study of technology, researchers have drawn comparisons with both substance addiction (Anderson, 2001; Brenner, 1997) and behavioural addictions (Cao et al., 2011; Young, 1999), often adopting a clinical or diagnostic perspective.

Technology adoption is behavioural and does not have the same physiological component as substance use (Shapira et al., 2003). For that reason, approaches developed for treating substance addiction are not readily transferable to the study of technology. Researchers have instead drawn on models of behavioural addiction, particularly those concerned with impulse-control disorders, to describe technology-related addiction (Divian, 2012; Warden et al., 2004).

Earlier work on television offers a useful starting point. McIlwraith et al. (1991) examined the unintended effects of television viewing, while McIlwraith (1998) suggested parallels between television and Internet addiction. A growing body of research has since argued that technology addiction may exist and may be widespread (Aljomaa et al., 2016; Lortie, 2013). It can be understood as a combination of behavioural and cognitive processes involving interaction between people and machines. The activity may be passive, such as watching television, or active, such as playing computer games (Widyanto & Griffiths, 2006). Its educational dimension, however, remains under-researched.

Research on students has considered their use of technology not only as learners, but also as members of wider society. This work includes Internet-based gambling (LaPlante et al., 2009), gaming on MMORPG platforms (Barto & Wang, 2010; de Kervenoael et, al.), and the developing literature on 'Facebook addiction' or 'Facebook intrusion' (Andreassen et al., 2012; Elphinston & Noller, 2011). The latter also draws on Beaudry and Pinsonneault's (2005) work on emotional attachment in technology adoption.

Interactive features are frequently associated with a greater propensity to develop technology-related addiction (Wang et al., 2015). Common examples include multi-user domains, chat rooms, bulletin boards, online games, cybersex/cyberporn and gambling (Young, 2008). As product and service development has become more open and user-centred, the opportunities for repeated and prolonged use have also increased. Research on technostress (Saleem et al., 2024; Asad, 2023; Savaş et al., 2025) captures part of this problem by showing how technology consumes users' time and both shapes and reflects the reasons for which it is used.

We used the Syndrome Model (Shaffer et al., 2004), together with Barto and Wang's (2010) work on addiction, to develop an exploratory list of themes for the study. These themes were incorporated into TAM2 to extend its scope. The Syndrome Model takes a causal or origin-focused approach, identifying recurring characteristics of addictive behaviour (Table 1). Other frameworks were considered. Lowry et al.'s (2013) Hedonic-Motivation Systems Adoption Model (HMSAM), for example, responds to criticism that TAM is poorly suited to hedonic information systems and social networking. Its emphasis on gamification, however, made it less appropriate for a study focused on learning rather than games. We also considered the Internet Process Addiction Test (IPAT) developed by Northrup et al. (2015), but this instrument focuses primarily on the person rather than the technology. Fathema et al.'s (2015) extended approach was therefore better suited to the educational setting.

Table 1
Condensed characteristics and manifestations of technology-related dependency.

Dimension	Main characteristics	Illustrative manifestations
Background vulnerabilities	Emotional distress, self-regulation difficulty, environmental and social pressures	Anxiety, loneliness, fatigue, peer pressure and difficulty regulating impulses
Access and reinforcement	Continuous access, immediacy and repeated rewards	Always-on availability, instant gratification and habitual checking
Escapism and identity	Technology used for distraction, fantasy or alternative identity	Role play, alter egos and avoidance of uncomfortable situations
Behavioural consequences	Loss of control, denial, mood change and conflict	Compulsive use, irritability, family conflict and reduced face-to-face interaction
Social withdrawal and dependency	Reduced offline activity and increasing reliance on digital connection	Loss of interest in physical interaction and feeling unable to function without access

Source: Authors (2026).

Foundations of the technology acceptance model

TAM has its origins in the theory of reasoned action (TRA), developed by Ajzen and Fishbein (1980; 1984). TRA proposes that behaviour is shaped by an intention to act, which in turn reflects attitudes towards the behaviour and the subjective norm. Ajzen (1991) extended this account through the theory of planned behaviour (TPB), allowing it to address actions that are not entirely voluntary. Perceived behavioural control (PBC) was added as an independent predictor of intention. It accounts for situations in which people lack the control or resources needed to perform the intended behaviour effectively (Hu, 2002).

These models have been used to explain user behaviour across education, e-commerce, groupware and telemedicine (Yui et al., 2007; Riffai et al., 2012). Much of this research has aimed to increase use, identify barriers to it and understand users' intentions to adopt a technology (Venkatesh et al., 2003).

The technology acceptance model (TAM)

TAM links perceived usefulness and ease of use with attitudes, intentions and actual computer-use behaviour (Davis, 1989). In the model, behavioural intention is shaped by attitude and perceived usefulness, while attitude is influenced by perceived ease of use (PEOU) and perceived usefulness (PU). These variables replace the attitude determinants used in TRA. TAM is therefore concerned with predicting whether a tool will be accepted and with identifying changes that might make it more acceptable. It has been applied across a wide range of end-user technologies.

Venkatesh and Bala (2008) extended the original model through TAM2, which explains perceived usefulness and intentions to use a system in terms of social influence and cognitive-instrumental processes.

Our study takes this extended model in a different direction. In practice, freedom to act is constrained by technical ability, time, environmental and organisational conditions, and less conscious habits such as digital dependence (Bagozzi, 2007).

UTAUT, UTAUT2, TOE and VAM broaden TAM by incorporating contextual, organisational, hedonic and value-based factors (Kim et al., 2007; Tornatzky & Fleischer, 1990; Venkatesh et al., 2003, 2012). None, however, directly explains the point at which sustained adoption becomes dependency or causes harm. We therefore retained TAM2 and added addiction-related constructs drawn from the Syndrome Model.

Fig. 1 brings these non-traditional TAM elements together. The components within the TAM2 box have already been extensively tested and reported in the literature (see Chi et al., 2011); the additional constructs are the focus of the present study.

Unpacking the intellectual construct

The variables on line A of Fig. 1 have not previously been incorporated into TAM and are the main concern of this paper. Those within the inner rectangle form the established TAM2 core, where 'use outcomes' have commonly been used to address questions of adoption. The following discussion briefly defines each variable, while Fig. 1 shows how the new elements relate to one another.

Social influence processes

- Subjective norm: perceived expectations of important others (Fishbein & Ajzen, 2010).
- Self-image: the extent to which use enhances perceived social status (Rogers, 2003).
- Voluntariness: the extent to which adoption is perceived as non-mandatory (Agarwal & Prasad, 1997; Hartwick & Barki, 1994).

Cognitive instrumental processes

- Relevance to need: the system's perceived relevance to the user's purpose (Venkatesh & Davis, 2000).
- Output quality: the perceived quality of system performance (Venkatesh & Davis, 2000).
- Experience: accumulated familiarity with a system (Venkatesh & Bala, 2008).
- Perceived usefulness: the expectation that system use will improve performance (Davis, 1989).
- Perceived ease of use: the degree of comfort associated with the use of the system, which, in other TAM studies, is sometimes referred to as 'effort expectation.'
- Behavioural intention and use: conscious plans to use a system and subsequent usage behaviour (Wu et al., 2008).

Traditional acceptance models are good at explaining why people adopt systems. They say much less about the point at which continued use becomes a dependency, a burden or a source of harm.

Research design

We used purposive convenience sampling. Participants were undergraduate business-school students aged 18 or over at a Scottish business school. To be eligible, they had to use Blackboard and university email, own a smartphone and use Facebook. The sampling frame was therefore defined by programme, institution and technology use rather than drawn randomly from the wider higher-education population.

Data were collected through a structured questionnaire. The sample was 47.3% male and 52.7% female, broadly reflecting the profile of the university. Most respondents (83%) were aged 18–19, 9% were aged 19–20, and the remaining 8% were mature direct-entry students who were over 20 when they began their degree. All met the university's entry requirements. This setting allowed us to compare technologies used in two distinct contexts: mandatory university systems (the virtual learning environment and university email) and voluntary personal systems (smartphones and social media).

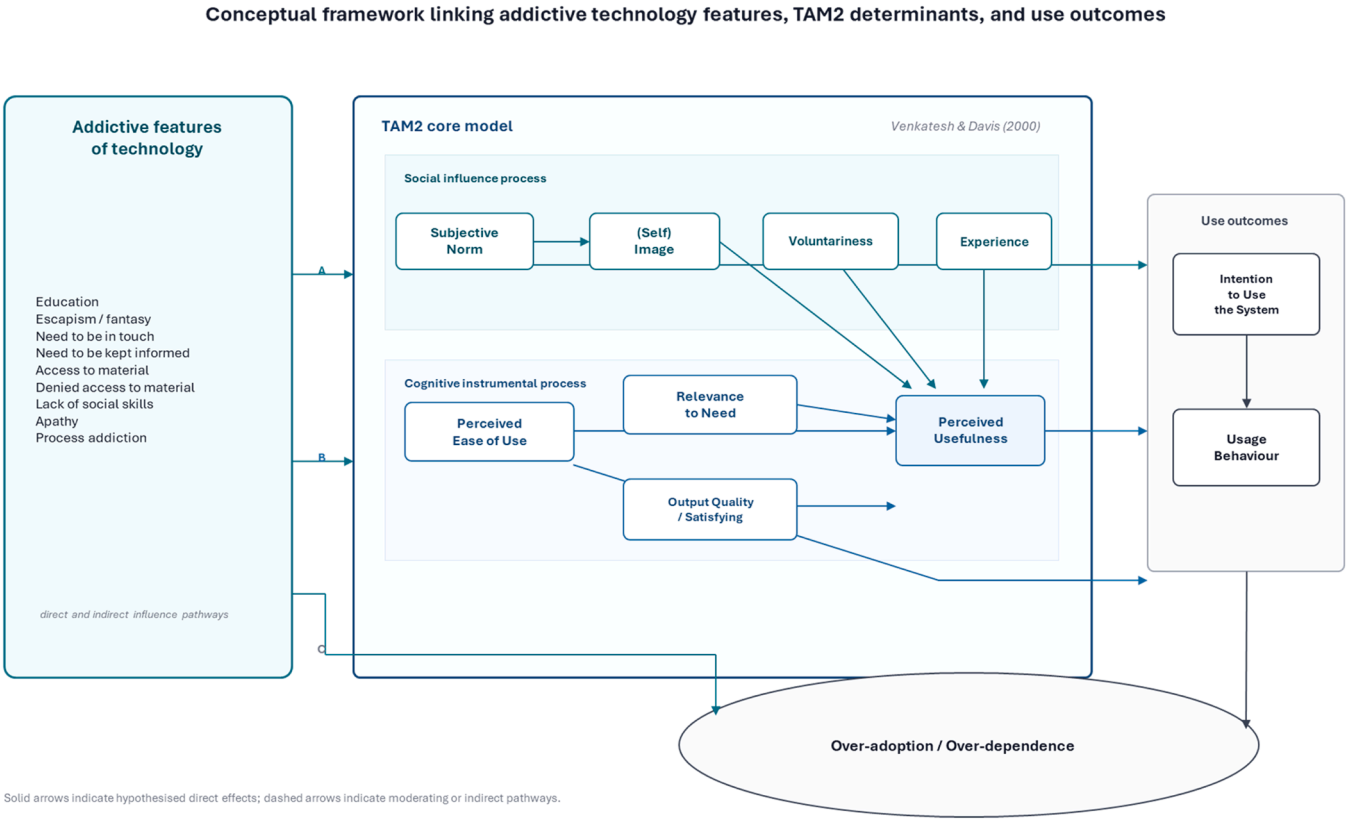

Fig. 1. Intellectual constructs developed by authors (2025).

RQ1 asks whether higher-education students show signs of digital dependency. Grounded in behavioural addiction theory, the analysis compared reported use of two mandatory institutional systems (Blackboard and university email) with two voluntary personal technologies (smartphones and social media), where patterns of use may be more likely to reflect addictive tendencies.

RQ2 asks whether students respond differently to mandatory and voluntary systems. The question follows from TAM's voluntariness dimension. The SEM results show that voluntary personal technologies are used more often and produce stronger emotional responses than mandatory institutional systems. Their social and emotional relevance may make personal technologies more susceptible to over-adoption, where repeated engagement can become difficult to regulate. By adding features such as escapism, compulsive checking and emotional attachment to TAM, the model connects user behaviour with both system design and psychological experience.

The survey examined why and how respondents used four IT systems over a fixed period. Participants reported separately on university-provided and personal systems, and personal and academic smartphone use were recorded separately to reduce double-counting. The students began their studies in September 2021 and completed the survey in their fourth year.

Perceptions were collected through a semi-structured online questionnaire administered via SurveyMonkey. Drawing on Meerkerk et al.'s (2006) Internet addiction framework, the instrument included a 14-item unidimensional self-report scale. Responses ranged from 0 (never) to 4 (very often). The items covered loss of control, cognitive and behavioural preoccupation, withdrawal symptoms, coping or mood modification, and interpersonal and intrapersonal conflict.

The design carries a risk of selection bias and limits external validity. Business students may be particularly career-oriented, instrumentally focused and accustomed to goal-directed technology use. These characteristics could strengthen self-regulation or create an 'instrumental override', in which academic and career priorities constrain maladaptive use despite exposure to persuasive platform features. The non-significant SEM path may therefore be partly specific to this sample. The findings should not be generalised uncritically to other disciplines, institutions, age groups or national contexts.

Of the 674 eligible students, 316 completed the questionnaire, giving a response rate of 47%. The 43-item instrument covered demographics, patterns of use, dependence, effects on personal and academic life, voluntariness and over-adoption. The analysis involved data screening and treatment of missing values, PCA with varimax rotation, and SEM of the relationships between participant information, influence factors and behavioural outcomes.

Model fit was assessed using several indices rather than a single statistic: the Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI) and Root Mean Square Error of Approximation (RMSEA). Under established conventions, GFI values approaching .90 suggest acceptable fit, AGFI values nearer .90 indicate stronger parsimony-adjusted fit, and RMSEA values below .08 indicate acceptable approximation.

We began by examining missing values. Fig. 2 shows several instances of missing data. Little's (1988) Missing Completely at Random (MCAR) test indicated that the values were not missing completely at random ($p = .000$), a pattern also visible in Fig. 2(1b). Five multiple imputations were therefore used. The imputation model drew on the observed questionnaire variables later grouped into participant-information, influence-factor and behaviour blocks, allowing variables associated with both missingness and the target measures to inform the estimates. The final analytical dataset used the average of the five imputed values. The archived output does not contain a variable-by-variable imputation specification. This limits reproducibility, and future replications should report the full predictor matrix, imputation method, convergence diagnostics and pooled estimates rather than only an averaged completed dataset.

Questionnaire items were grouped into participant information (5 items), influence factors (45 items) and behaviour (29 items). PCA with varimax rotation was used to create composite components. Retention decisions drew on the Kaiser criterion, Monte Carlo parallel analysis, scree-plot inspection and explained variance. KMO and Bartlett's tests were used to assess factorability.

Finally, we constructed a structural equation model (SEM) to test whether participant information and influence factors affected behaviour. The composite variables extracted through PCA were used as indicators of the latent variables.

Results

The analysis addressed the two research questions introduced earlier: whether digital dependence is evident among higher-education students (RQ1), and whether students respond differently to mandatory and voluntary systems used in education (RQ2).

The participant-information analysis began with five items. Table 2

Table 2
Participant-information components retained for analysis.

Component	Eigenvalue	Variance (%)	Cumulative (%)	Decision
1	2.124	42.488	42.488	Retained
2	1.296	25.928	68.416	Retained
3–5	< 1.000	31.584	100.000	Not retained

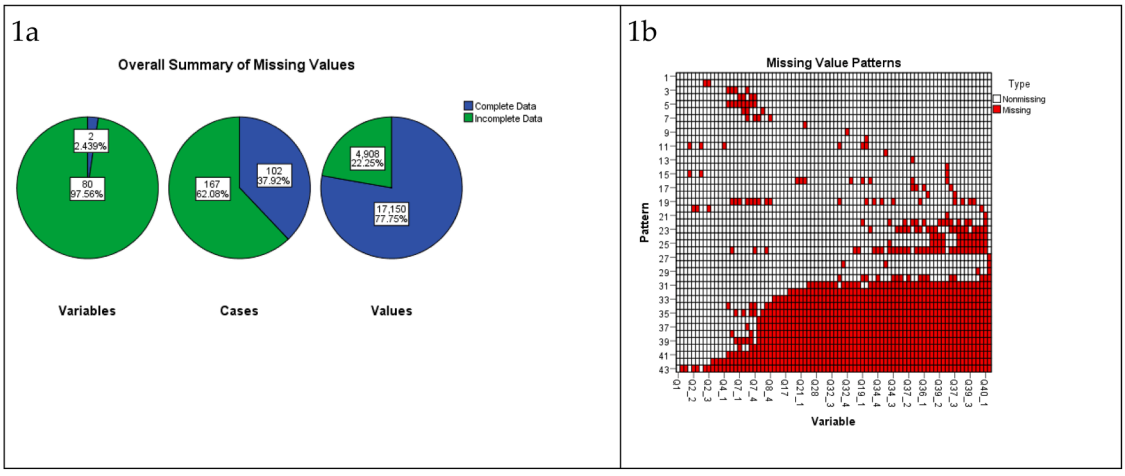

Fig. 2. Missing values.

reports the component eigenvalues, the proportion and cumulative proportion of variance explained, and the corresponding Monte Carlo parallel-analysis values.

The Kaiser criterion initially supported retaining two components because only two eigenvalues were greater than 1. Parallel analysis led to the same decision: only the first two eigenvalues exceeded their corresponding simulated values (for the second component, 1.296 > 1.07). The scree plot also showed a clear break after the second component. Together, the retained components explained 68.416% of the variance.

PCA interpretation

For clarity, the extracted influence components are described below in conceptual terms.

1. Social connectivity and need to remain informed
2. Emotional reassurance and accessibility
3. Functional utility and task completion
4. Social image and peer visibility
5. Academic dependency and course coordination
6. Habitual checking routines
7. Peripheral attitudes (removed in final model)
8. Habit reinforcement
9. Convenience orientation
10. Always-on device immediacy

The PCA of participant information retained two components. Both were above the parallel-analysis threshold and together explained 68.416% of the variance (Table 2).

The Kaiser criterion, parallel analysis and scree plot each supported this two-component solution.

The KMO value for participant information was marginal (.603), although Bartlett's test was significant and all communalities were above .600 (Table 3). The construct should therefore be interpreted with care. KMO and Bartlett's test assess factorability, not internal consistency.

Parallel analysis initially supported 11 influence-factor components, accounting for 64.557% of the variance. The eleventh component was removed because only three items loaded marginally above .300. The final ten-component solution explained 61.508% of the variance (Table 4).

Ten principal components were extracted for the influence factors. As Table 5 shows, the KMO value was acceptable (.724) and Bartlett's test was statistically significant, meeting the conditions for factor analysis. Most communalities were above .500; the two lower values still exceeded .300.

The behavioural analysis contained 29 items. The scree plot in Fig. 3 (2c) confirms the parallel study of the five principal components, as there was a clear break from the sixth component and above. Parallel analysis supported five components (1.924 > 1.3788), which together explained 55.972% of the variance (Table 6).

Five behavioural components were retained. Q15 and Q33_4 were removed because their communalities fell below .300. After their removal, the solution explained 58.868% of the variance. KMO was acceptable (.728), and Bartlett's test was significant (Table 7), although a substantial proportion of variance remained unexplained.

Table 3
Participant-information PCA diagnostics.

Diagnostic	Result	Interpretation
KMO	.603	Marginally acceptable; shared variance is relatively weak
Bartlett's test	$\chi^2 = 277.273$, df = 10, $p < .001$	Correlations are sufficient for factor analysis
Communality range	.610-.739	All items exceed the .300 minimum
Components retained	2	Together explain 68.416% of variance

Table 4
Influence-factor component-retention summary.

Components	Eigenvalue range	Cumulative variance (%)	Decision
1–10	7.941–1.478	61.508	Retained
11	1.372	64.557	Removed: weak item loadings
12–15	1.290-.928	74.264	Not retained by parallel analysis

Table 5
Influence-factor PCA diagnostics.

Diagnostic	Result	Interpretation
KMO	.724	Acceptable sampling adequacy
Bartlett's test	$p < .001$	Correlations are sufficient for factor analysis
Communality range	.416-.735	All items exceed .300; two are below .500
Components retained	10	Retained solution explains 61.508% of variance

Cronbach's alpha and McDonald's omega were not preserved in the archived outputs and cannot be reconstructed from communalities and factor loadings. The components should therefore be regarded as exploratory. Future analyses should report reliability coefficients together with item-total diagnostics and confidence intervals.

Table 8 summarises the latent components. Item-level means, standard deviations and loadings are provided.

Infl_7 and Beh_4 were excluded because they performed poorly both statistically and conceptually. Fig. 4 shows the final SEM.

Participant information was a significant predictor of behaviour, but the path from influence factors to behaviour was not significant ($p = .510$). The covariance between the exogenous variables was small but significant ($p = .002$, $r = .060$). Overall model fit was mixed: GFI was acceptable (.903), AGFI was below the preferred threshold (.866), and RMSEA indicated acceptable approximate fit (.077; Table 9).

SEM theoretical implications

Participant information significantly predicted behaviour, whereas influence factors did not ($p = .510$). This result challenges a technologically deterministic account: persuasive or ostensibly addictive design features do not necessarily produce problematic behaviour. Their effects are likely to depend on user agency, social and institutional context, digital literacy and self-regulation. Academic and career priorities may also provide an instrumental override that constrains maladaptive use.

The fit statistics support a provisional rather than a definitive causal interpretation. In particular, the below-threshold AGFI suggests that the model may omit relevant mediators, moderators or interaction effects.

Future research should test digital fatigue, digital literacy, self-regulation, resilience, academic pressure, social norms and disciplinary differences as possible mediators or moderators. The average SEM path does not rule out indirect, subgroup-specific or context-dependent effects.

We compared voluntary and mandatory technologies by frequency of use. Personal systems were used most often: 77% of respondents used smartphones and 45% used social media >20 times per week. The equivalent figures were 9% for Blackboard and 15% for university email. The pattern suggests that communication and connection with personal communities are central to students' use of social media. Further analysis using the Kruskal–Wallis test did not identify significant differences within subgroups such as age.

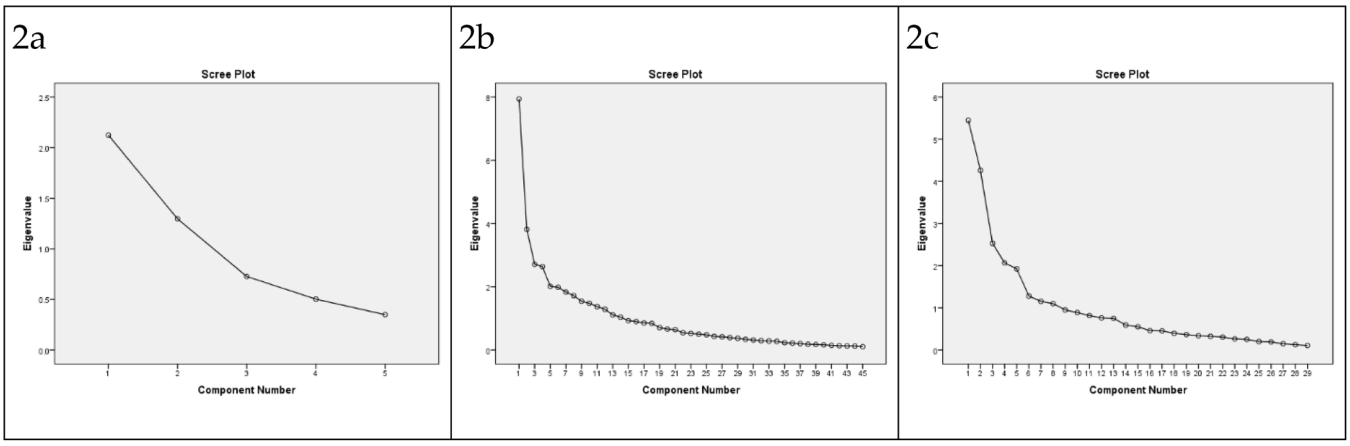

Fig. 3. Scree plots.

Table 6
Behavioural component-retention summary.

Components	Eigenvalue range	Cumulative variance (%)	Decision
1–5	5.449–1.924	55.972	Retained
6–8	1.280–1.100	68.160	Not retained by parallel analysis
9	.950	71.437	Not retained

Table 7
Behavioural PCA diagnostics.

Diagnostic	Result	Interpretation
KMO	.728	Acceptable sampling adequacy
Bartlett's test	$p < .001$	Correlations are sufficient for factor analysis
Items removed	Q15 and Q33_4	Communalities were below .300
Communality range after removal	.318-.728	All retained items exceed .300
Variance explained	58.868%	Adequate for exploratory analysis, but substantial variance remains unexplained.

Table 8
Summary of latent components.

Component	Plain-language meaning	Items (n)
Info_1	Participant profile	3
Info_2	Prior technology-use profile	2
Infl_1	Social connectivity and staying informed	8
Infl_2	Emotional reassurance and accessibility	6
Infl_3	Functional utility and task completion	5
Infl_4	Social image and peer visibility	6
Infl_5	Academic dependency and course coordination	4
Infl_6	Habitual checking routines	3
Infl_8	Convenience and immediacy	2
Infl_9	Routine reinforcement and social availability	4
Infl_10	Always-on device immediacy	3
Beh_1	Discomfort when access is restricted	8
Beh_2	Routine and repeated engagement	6
Beh_3	Intensity and frequency of interaction	7
Beh_5	Perceived importance and dependency	4

Students also used personal technologies for longer periods and rated them as more important than institutional systems (Figs. 5 and 6). Most interactions lasted no more than ten minutes, but smartphone sessions averaged more than two hours. Smartphones were judged the most important technology. Blackboard and university email were valued mainly for academic communication, assessment and participation in courses.

Fig. 6 shows how respondents ranked mobile phones, Facebook, email and Blackboard. The gap between voluntary and mandatory technologies is clear, although not unexpected. University systems have not fully bridged that gap: they remain less accessible within the mobile and social-media spaces where many student discussions take place.

Mobile phones were rated as the most essential technology. However, many respondents also regarded Blackboard/VLE and email as necessary, probably because these systems support their courses and communication with tutorial groups. At the same time, some students described Blackboard and email as unnecessary, and 37% regarded Facebook/Twitter as unimportant. Very few considered the mobile phone insignificant. This pattern may reflect different institutional views of technology in learning. Technology can broaden how and where students learn. However, it can also be used primarily to reduce costs, extend reach or digitise existing practice without developing genuinely new approaches to teaching and learning.

Responses to technology becoming unavailable varied sharply by system (Figs. 7 and 8). >40% reported strong frustration when they could not use a smartphone, and smartphones produced the highest proportion of 'devastated' responses when taken away. By comparison, loss of Blackboard or email was more likely to cause frustration or agitation than comparable emotional distress.

The results point to a useful distinction between functional and emotional dependency. Blackboard and university email create functional dependency because students need them to receive information, submit assessments, meet deadlines and progress through their studies. Students may have little emotional attachment to these systems, but institutional processes make access necessary. When the systems are unavailable, the usual response is frustration, annoyance, or agitation: the interruption affects tasks, compliance, and academic progress rather than identity, reassurance, or social connection.

Personal technologies, especially smartphones and social media, work differently. They are tied to students' sense of self, social presence, reassurance, belonging, peer visibility and availability to others. Their role extends beyond completing tasks; students use them to maintain relationships, regulate mood, follow their social lives and stay connected to their communities. This helps explain why losing access to a smartphone can produce responses such as feeling 'devastated', while losing Blackboard is more often experienced as a practical frustration.

This distinction clarifies RQ2. Mandatory and voluntary systems differ not only in frequency of use, but also in the kind of dependency they create. Institutional technologies impose reliance through academic necessity. Personal technologies encourage it through emotional attachment and social embeddedness. Universities should therefore be cautious about trying to make institutional platforms resemble social media. Such changes might increase engagement, but they could also

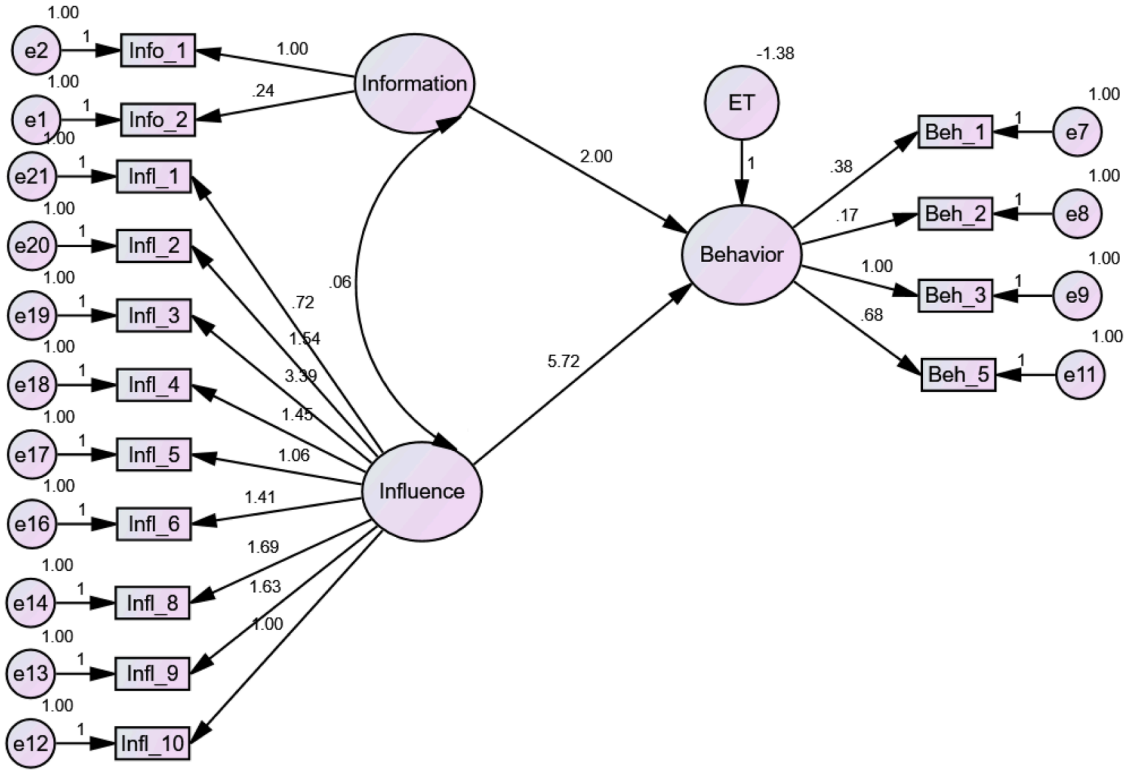

Fig. 4. Structural equation model.

Table 9
Key structural paths and model-fit summary.

Model element	Estimate	p-value	Reader interpretation
Participants' information - behaviour	2.005	< .001	Statistically significant
Influence factors - behaviour	5.722	.510	Not statistically significant; supports a mediated/moderated interpretation.
Covariance between exogenous variables	.060	.002	Small but statistically significant association
GFI	.903	-	Acceptable
AGFI	.866	-	Below preferred .90 threshold
RMSEA	.077	-	Mediocre but acceptable fit

import design practices that intensify compulsion, anxiety, social comparison and over-attachment.

For higher education, the task is to improve the usability, accessibility, reliability and pedagogical relevance of mandatory systems without trying to make them emotionally addictive. Innovation probity directs attention towards purposeful academic engagement rather than

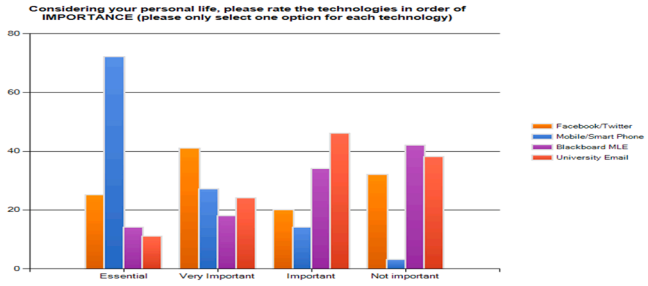

Fig. 6. Importance of technology.

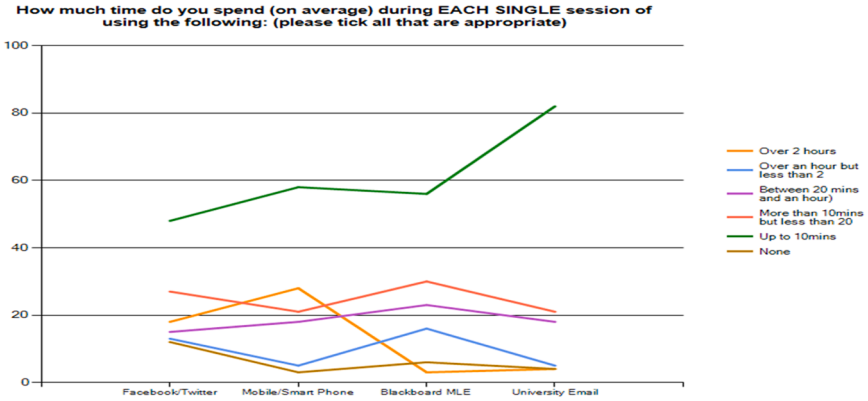

Fig. 5. Time spent on each type of technology.

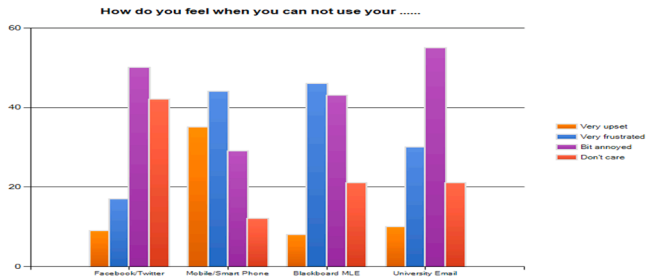

Fig. 7. How respondents feel when technology cannot be used.

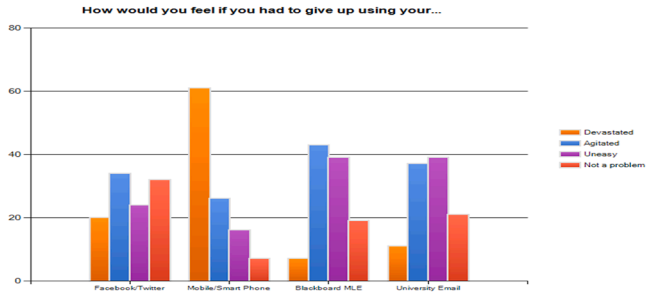

Fig. 8. How respondents would feel if technology were to be 'taken away'.

affective capture. Educational technologies should support learning without turning functional necessity into emotional dependency.

When asked which technology most dominated their lives, students chose their personal mobile phones. Fifty-nine per cent felt frustrated when they could not use or access them. Mandatory systems also caused frustration and annoyance when unavailable, a notable finding given that students were required to use them. Family complaints provided another indicator: 81% reported that relatives had complained about excessive phone use or its effect on family interaction. The equivalent figure for Facebook/Twitter was 39%, while university systems featured very little. These reports are consistent with digital dependency.

When students were asked how they would feel if a technology were taken away, the personal mobile phone produced the largest number of responses in the 'devastated' category (Fig. 8). The term was deliberately chosen to represent the strongest emotional response, and respondents were willing to use it.

Routine checking followed a clear order: smartphones first, then social media and university email (Fig. 9). Smartphones were checked most frequently, with 46% of respondents doing so every hour. Twenty-seven per cent checked social media every two to six hours. University email was checked less often; 42% reported intervals of about two days.

These patterns do not demonstrate addiction, but they do show habitual and potentially dependency-forming engagement, particularly with personal technologies.

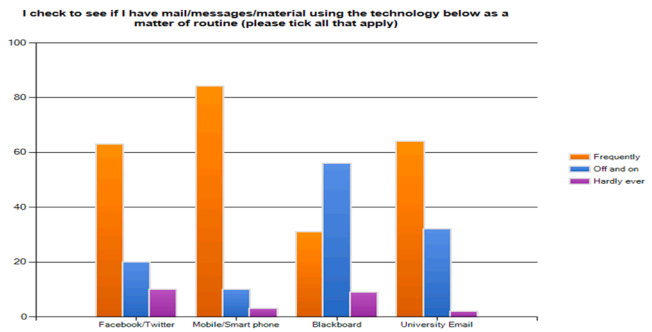

Fig. 9. Frequency of 'checking' technology as a matter of routine.

To explore reliance on each technology, we asked respondents how long they could go without checking it (Fig. 10). Blackboard was checked least often and had the longest interval between checks. Mobile phones were much more pervasive, with most respondents checking them at least hourly, which is consistent with the reported response to losing access. Facebook/Twitter produced a more even spread across the time periods, suggesting differing views of how essential it was. Overall, the results indicate increasing reliance on regular technological contact.

>60% of respondents checked their smartphone as soon as they woke, compared with 40% for social media and fewer than 30% for mandatory systems (Fig. 11). Personal technologies were also commonly checked before bed, whereas institutional systems were accessed mainly when needed.

Frequent checking was linked to social availability: 78% allowed friends to contact them at any time, and 76% wanted to remain continuously available. Smartphones were experienced primarily as tools rather than as a means of relaxation, while institutional systems were generally seen as chores.

Table 10 records how respondents felt after using each technology. For most, mood did not change. Facebook/Twitter and mobile-phone use were nevertheless more likely to make respondents feel 'happy', or at least 'not sad'. This suggests that these technologies can have a mood-related role and may help motivate or support students when integrated appropriately into daily life.

Open-ended questions were used to explore the wider effects of technology. Asked whether they still felt like going out and socialising after using it, 96.1% said that they did, regardless of the technology concerned. The remaining respondents said that technology could discourage them from going out because they would use it instead.

Discussion

One implication of the findings is that dependency-like behaviour has become normal among contemporary students. Actions that might once have been treated as warning signs—checking a phone immediately on waking, feeling distressed when access is removed, or receiving family complaints about excessive use, are not necessarily recognised by students as unusual or problematic. The study does not reveal a simple pattern of students describing themselves as 'addicted'. It shows something less explicit: behaviours associated with dependency have become part of everyday routines, social expectations and identity.

The Syndrome Model helps to interpret this pattern because it draws attention to behaviour, contextual reinforcement, difficulty with impulse control, constant access to the stimulus, and denial or limited recognition of a problem. Here, the issue may be less a clinical form of

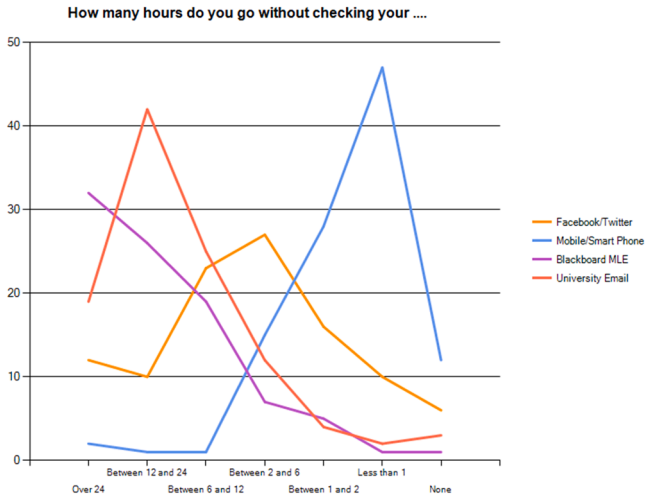

Fig. 10. Duration between 'checking' different technologies.

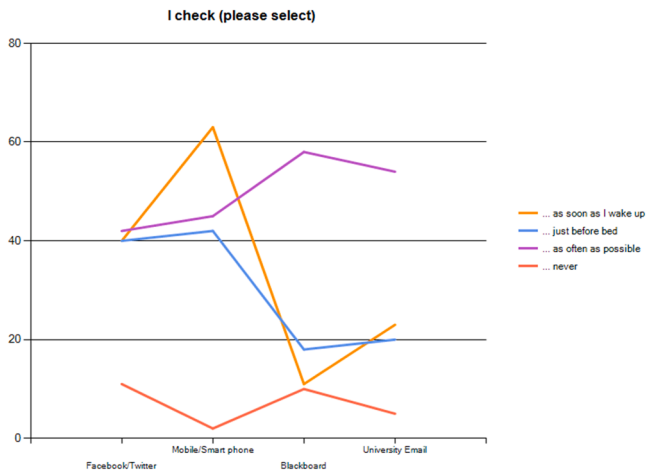

Fig. 11. When communication technology is 'checked'.

Table 10
Feelings invoked by the use of each type of technology.

Technology	Happy	The Same as before I Used It	Sad
Facebook/Twitter	30.9%	66%	3.2%
Mobile/Smartphone	41.7%	58.3%	0%
Blackboard	13.3%	80.6%	6.1%
University Email	13.4%	84.5%	2.1%

denial than a culturally normalised failure to recognise dependency. Students may not deny constant connectivity; they may not regard it as dependency. For a post-pandemic generation, being reachable and responsive online has become part of ordinary social participation.

This interpretation adds a second layer to the paper's contribution. The non-significant direct path between addictive features and behaviour does not show that dependency is absent. It may instead suggest that the behaviour has become so normalised that students no longer see it as exceptional, risky or addictive. The concern therefore extends beyond individual overuse to a cultural and institutional environment in which continuous connection is expected. This is the basis of the tipping-point argument. Higher education may now operate in a setting where digital dependency is experienced as routine rather than deviant. Responsible technology practice needs to recognise these signs before they are further built into pedagogy, platform governance and student expectations.

Across the findings, mandatory and voluntary adoption produced different attitudes and experiences. Mandatory systems were more regulated and 'work-like', while personal technologies were more closely associated with habit, ritual and possible digital dependence. Higher education may need to reconsider how both are used. Decisions to develop or encourage educational technology should take account of over-adoption and dependency, not only uptake.

The engagement gap should not be addressed by making university systems as 'sticky' as commercial platforms. Gamified loops, excessive notifications, manufactured urgency and social comparison could turn functional necessity into emotional dependency and add to burnout, fatigue and cognitive overload.

A more appropriate aim is proportionate and purposeful engagement. Higher education institutions should improve accessibility, reliability and usability while avoiding design practices that exploit anxiety or imply permanent availability. Engagement measures should not be treated as substitutes for evidence of learning, and default notifications should limit interruption rather than maximise return visits.

The paper identifies a paradox in student technology use. Students may show recognisable behavioural signs of digital dependency without describing or interpreting those behaviours as addiction. The SEM result is therefore informative rather than simply a failure to detect the phenomenon. The non-significant relationship between addictive features and behaviour suggests that problematic use cannot be reduced to a deterministic sequence in which platform design automatically causes addiction. Context, habit, social expectations, emotional attachment and the normalisation of constant connectivity are also likely to shape behaviour.

Conceptual framework - innovation probity

Responsible technology research has raised growing concern about the platformisation of education, as learning comes to depend on private infrastructure, behavioural analytics, nudging architectures and engagement measures (Williamson, 2016).

Universities consequently need stronger normative tools for judging whether a technology should be adopted. We describe one such tool as innovation probity. Mainstream educational technology discourse often assumes that innovation is beneficial; innovation probity instead asks whether a particular innovation is justified, proportionate and ethically defensible in practice.

Innovation probity shifts attention from successful adoption to socio-technical responsibility. It considers not only what technologies enable, but also what they demand from users in attention, emotional labour, dependence, behavioural adaptation and opportunity cost. Drawing on the AREA framework (EPSRC, 2026), we define innovation probity as an obligation to design, procure and deploy educational technologies honestly, proportionately and with regard for student well-being.

The AREA framework offers a practical way to apply innovation probity to the procurement, design and implementation of educational technologies.

Anticipation asks institutions to consider unintended consequences before they purchase or embed a system. Procurement of a learning management system, for example, should address more than cost, functionality, scalability, analytics and integration. A responsible technology assessment should also ask whether the system increases notification load, encourages repeated checking, intensifies surveillance, fragments attention or creates dependency. Reflexivity asks whether additional digital activity improves learning or merely extends expectations of availability. Engagement requires structured student and staff feedback on fatigue, accessibility, workload and value. Action turns those findings into safeguards, such as reducing unnecessary notifications, limiting the use of engagement measures, protecting offline learning and sustaining blended provision.

Innovation probity is not an argument against digital innovation. It requires educational technology to be justified, proportionate and humane. The question is not simply whether a platform can increase use, but whether the kind of use it encourages is educationally legitimate and compatible with student well-being.

Theoretical contribution

The study makes three connected theoretical contributions.

First, it takes TAM beyond pre-adoption beliefs and behavioural intentions to consider post-adoption outcomes. Acceptance and well-being are not the same: a system can be useful, accepted and frequently used while still generating fatigue, compulsion or dependency.

Second, we distinguish functional from emotional dependency. The distinction helps to explain why an institutional system may be necessary but frustrating, while a personal system may be reassuring yet difficult to put aside.

Third, the results challenge the deterministic assumption that persuasive design automatically produces problematic behaviour. The non-significant SEM path suggests that agency, social norms, context and personal capacities all shape the outcome.

Responsible technology implications for HEIs

As universities become more dependent on platform providers and integrated data systems, procurement decisions need to consider behavioural effects, privacy, demands on attention and student well-being alongside functionality and price. Higher education institutions should:

1. Include well-being criteria in procurement decisions.
2. Audit notification load, frictionless engagement loops, and attention capture mechanisms;
3. Design blended learning with intentional offline spaces;
4. Train staff in sustainable digital pedagogy;
5. Embed digital self-regulation and literacy into curricula;
6. Monitor fatigue and burnout alongside satisfaction metrics.

Limitations

The timing of the study is an important limitation. Data were collected before large language models and generative AI became part of routine student work. AI may deepen dependency by making academic activity continuously available, personalising prompts and extending habitual interaction into writing, search and decision-making. It could also reduce cognitive load or replace some uses of other platforms. Replication should compare cohorts from before and after the widespread adoption of generative AI, with particular attention to any shift between functional and emotional dependency.

Other methodological limitations also need to be acknowledged. Self-reported measures are vulnerable to recall error and social desirability bias, and the cross-sectional design does not support causal inference. The purposive convenience sample came from one Scottish business school, creating selection bias and limiting generalisability; career orientation and instrumental self-regulation may partly account for the non-significant structural path. In addition, the participant-information KMO was marginal (.603), the behavioural components explained 58.868% of the variance, and the archived outputs did not contain reliability coefficients or the full variable-by-variable imputation specification. Variables omitted from the model—including digital literacy, self-control, fatigue, disciplinary culture and socioeconomic context—may also mediate or moderate the observed relationships.

Conclusion

The study does not establish clinical addiction. It does, however, identify culturally normalised indicators of digital dependency, including habitual checking, distress when access is interrupted, conflict and a perceived need for constant connection. RQ1 is therefore supported at the level of problematic use and dependency indicators. RQ2 points to two forms of reliance: institutional systems create functional dependency, while personal technologies produce stronger emotional attachment.

Innovation probity gives institutions a normative framework for asking whether digital systems serve a pedagogical purpose without imposing avoidable psychological or behavioural costs. The evidence suggests early signs of problematic dependency, especially with personal technologies. Mandatory systems, by contrast, tend to create functional reliance rather than emotional attachment.

The non-significant SEM path ($p = .510$) is central to the paper's theoretical contribution. Persuasive or immersive design features did not directly predict behaviour, challenging the deterministic view that platform features automatically create dependency. The finding instead directs attention to context, agency, self-regulation, digital literacy, social norms and instrumental priorities. Innovation probity translates that insight into a practical requirement: educational technology should remain proportionate, humane and tied to a clear pedagogical purpose.

Generative AI makes this question more pressing because it brings continuous digital interaction into writing, research, feedback and decision-making. Longitudinal and cross-disciplinary studies should compare pre- and post-AI cohorts, test fatigue and instrumental override as mediators, and examine whether AI increases dependency or redistributes it across platforms. The present findings provide a pre-LLM baseline for that work.

CRediT authorship contribution statement

Kevin Grant: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **David A. Edgar:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Des Doran:** Writing – review & editing, Validation, Methodology, Formal analysis.

Declaration of competing interest

All authors declare that they have no conflicts of interest. It was a self-funded study, and ethical permission for the case business school was obtained.

Acknowledgements

We are indebted to Nickolaos G. Tzeremes for his professional assistance with applying the statistical techniques employed in this paper, and to Professor Philip Powell for his earlier feedback.

During the preparation of this work, the author(s) used Grammarly to proofread and stylise the language in the paper. After using this tool, the author(s) reviewed and edited the content as needed.

Data availability

The data supporting this study's findings are available from the authors upon reasonable request. Still, given the nature of the questionnaire, restrictions apply to the availability of these data to protect student identity. The raw data will be anonymised, cleaned, and made available in Excel or CSV format.

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