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# Behavioural–Personality Framework for Adaptive E-Learning

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ORIGINAL STUDY

# Behavioural–Personality Framework for Adaptive E-Learning

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## ABSTRACT

**Purpose:** This study examines the limited integration of behavioural theory—specifically the Myers–Briggs Type Indicator (MBTI)—in the design of e-learning systems. MBTI is considered because personality variation influences learner motivation, engagement, and behavioural responses, yet most digital platforms rely on uniform instructional strategies. The study focuses on higher-education e-learning, where behavioural disengagement and psychological strain are increasingly reported.

**Design/methodology/approach:** A qualitative conceptual content-analysis approach is used to synthesise secondary evidence from peer-reviewed literature, policy documents, and institutional reports (2015–2024). The analysis identifies three theoretical categories—behavioural reinforcement, personality-based differentiation, and adaptive learning interaction—which shape the proposed behavioural–personality framework.

**Findings:** Three core patterns emerged: (1) behavioural reinforcement is inconsistently embedded within e-learning systems; (2) personality differences affect motivation, cognitive load, and persistence but remain insufficiently addressed; and (3) aligning reinforcement mechanisms with MBTI preferences can enhance self-regulation, emotional stability, and engagement. These insights support the need for a unified behavioural–personality model for digital pedagogy.

**Practical implications:** The study offers actionable guidance for universities, instructional designers, e-learning developers, and higher-education policymakers seeking to personalise learning pathways and strengthen student–teacher interaction in virtual learning environments.

**Social implications:** Embedding behavioural theory in e-learning promotes equity, digital inclusion, and psychological well-being by recognising diverse learner profiles.

**Limitations:** As a conceptual synthesis, the study excludes primary data and non-English sources; empirical testing across institutional and cultural contexts is recommended.

**Originality/value:** The paper proposes a unified behavioural–personality framework linking reinforcement theory with MBTI profiling to support adaptive, human-centred e-learning design.

**Keywords:** Behavioural theory, MBTI, E-Learning, Personality-Based learning, Student engagement

## 1. Introduction

The global educational landscape has entered an era of unprecedented digital migration. The shift from traditional classrooms to virtual environments, accelerated by the COVID-19 pandemic, has revolutionised how knowledge is created and delivered. Although e-learning enhances accessibility, affordability, and inclusiveness, it often overlooks the behavioural and psychological dimensions that shape learner engagement and instructor effectiveness. Many educators report rising levels of distraction, anxiety, and cognitive overload among students participating in digital courses [21, 31]. These challenges expose a critical gap between **technological adoption** and **behavioural understanding** in digital pedagogy. Furthermore, this digital shift has introduced complex social complications, such as reduced peer collaboration, weakened academic communities, and cultural misalignment between instructors and learners from

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different socio-economic backgrounds. These complications often manifest in unequal participation and emotional fatigue, indicating that e-learning success is not merely technical but inherently social and behavioural. These challenges also raise questions about inclusivity and the fairness of current e-learning systems, which may privilege certain personality types or learning preferences while disadvantaging others. Addressing this imbalance requires a theoretically grounded approach that connects behavioural reinforcement to personality dynamics.

Historically, behavioural theory has guided classroom management, motivation, and reinforcement strategies. Behavioural principles established by [45] and expanded through Bandura's [9] social learning theory have long informed classroom reinforcement and motivation strategies. Yet, within digital learning systems, such frameworks have received limited operational attention. The **Myers-Briggs Type Indicator (MBTI)**—grounded in Carl Jung's psychological-type theory—offers a structured approach to recognising individual differences in perception, judgment, and learning preference [23]. Integrating MBTI profiles into e-learning could personalise instruction, enhance retention, and reduce emotional strain. However, while elements of behaviourism are evident in gamification, adaptive LMS feedback, and micro-learning design, comprehensive integration of behavioural reinforcement with personality-based differentiation remains limited in e-learning research and practice. Consequently, digital pedagogy often fails to address the interpersonal and emotional depth that underpins sustainable learning relationships. Understanding these human dimensions is essential if e-learning is to evolve into an equitable and psychologically supportive environment. This aligns with broader regional research emphasising the transformation of doctoral education and leadership frameworks to meet evolving market and behavioural needs [5, 7]. Building on these insights, this study advances the argument that integrating behavioural empathy with personality-sensitive instructional design can operationalise digital motivation and engagement more effectively. Yet, few models explicitly operationalise behavioural mechanisms within personality-sensitive systems, leaving a critical theoretical and practical gap.

Accordingly, this paper proposes an integrated behavioural–personality framework that applies reinforcement theory and MBTI profiling to personalise e-learning design, offering a human-centric approach to improving motivation, engagement, and inclusivity.

Consequently, this study aims to evaluate the extent to which behavioural theory principles are neglected in e-learning and to propose MBTI-based assessment as a corrective pedagogical mechanism. The paper addresses three guiding questions:

**RQ1. What behavioural factors most strongly shape learner motivation, engagement, and performance in e-learning environments?**

**RQ2. Why do many e-learning platforms fail to incorporate behavioural frameworks such as MBTI, despite their potential to support personalised learning?**

**RQ3. How can MBTI-informed assessment approaches enhance learner engagement, self-regulation, and overall learning outcomes in digital settings?**

The ensuing sections review prior research on e-learning effectiveness, explore behavioural and personality-based theories, outline a qualitative conceptual methodology, and discuss theoretical as well as practical implications.

The proposed framework aligns with international educational transformation agendas such as Oman Vision 2040, the [20, 37], and China's Education Modernisation 2035 Plan, all of which emphasise behavioural adaptability and personalised digital learning.

## 2. Literature review

### *2.1. The evolution of e-learning*

The e-learning industry has witnessed exponential growth over the past decade. In 2019, its global market size reached **US $101 billion** and is projected to expand to **US $370 billion by 2026** [47]. This expansion is driven by advances in learning management systems, cloud computing, and mobile accessibility [36]. Fig. 1 illustrates the forecasted trajectory of this market, highlighting the diversification of e-learning segments. As shown in Fig. 1, this rapid market expansion underscores the urgency for pedagogical frameworks that evolve alongside technological growth. Yet, the literature suggests that behavioural and psychological adaptation has lagged far behind market development, creating a mismatch between digital infrastructure and human learning design.

Emerging instructional technologies, such as augmented and virtual reality, also reshape how learners engage in creative processes [14]. Despite its scalability, e-learning often fails to replicate the socio-emotional richness of face-to-face instruction. Studies report increased student isolation, demotivation, and reduced cognitive focus compared with traditional settings [15, 34]. The absence of structured behavioural management within digital environments exacerbates these challenges, especially among learners lacking self-discipline and

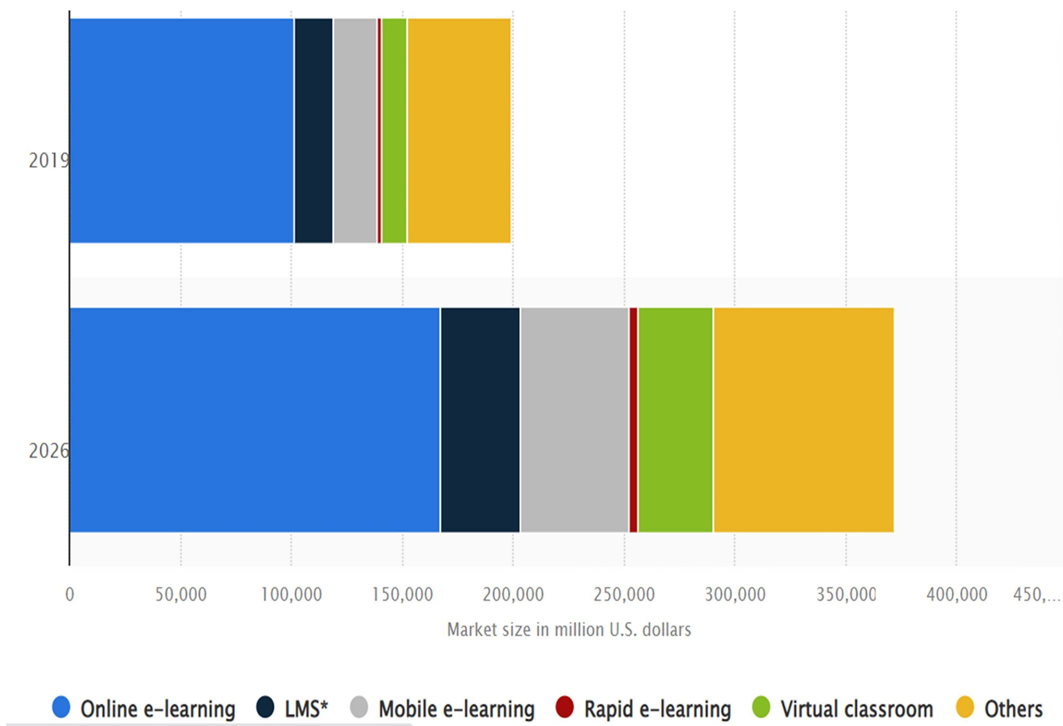


**Fig. 1.** Projected global e-learning market size (2019–2026).
Source: Statista [47].

time-management skills [28]. Additionally, the social detachment observed in online learning environments intensifies behavioural challenges. Learners from marginalised communities or with limited digital literacy experience higher dropout rates and lower engagement, highlighting the intertwined nature of behavioural and social barriers to effective e-learning. Behavioural responses, such as motivation and perseverance, are often moderated by contextual norms and collective learning values, particularly in multicultural education settings. Recent evidence from Omani higher education shows that students' acceptance of digital accounting courses depends not only on perceived usefulness and ease of use but also on psychological readiness and learning style compatibility [3].

### 2.2. Determinants of effective teaching and learning

Effective instruction depends on a combination of pedagogical skill, personality traits, communication clarity, and the psychological climate established in the learning space [32]. The digital transition disrupted these dynamics: instructors must now build rapport, enforce discipline, and deliver feedback through screens rather than physical presence. According to Schleicher [44], professional learning communities that reinforce reflective practice and behavioural awareness are crucial for sustaining quality teaching in online contexts.

Darling-Hammond [17] outlines six historical phases of effective-teaching research, ranging from early focus on teacher personality to contemporary emphasis on integrated professional knowledge. These phases mirror broader evolutions in education theory, as discussed by DeBoer [18], who traced similar paradigm shifts in the history of science education. Behavioural engagement—observable student participation and persistence—remains a consistent predictor of learning outcomes. Yet, e-learning studies rarely evaluate behavioural engagement through validated psychological frameworks such as MBTI. The current literature also underplays cultural and contextual diversity in behavioural responses to digital education. In collectivist societies such as Oman or other GCC contexts, social reinforcement, respect, and collaboration strongly shape motivation. Cultural alignment within digital pedagogy remains critical; evidence from Omani universities shows that motivation and ethical conduct are reinforced through culturally sensitive behavioural engagement strategies [6]. Beyond the GCC and Omani context, similar approaches have been documented in leading global studies. Research published in *Computers & Education* and *Internet and Higher Education* demonstrates that behavioural analytics, self-regulation theory, and AI-personalised learning frameworks significantly enhance learner engagement [13, 24]. Including such cross-regional evidence situates this study within the global discourse on digital pedagogy and behavioural learning analytics. Therefore, integrating behavioural theory with culturally informed MBTI application could ensure more equitable engagement across contexts. Alternatively, models such as Bandura's [9] social learning theory or Deci and Ryan's [19] self-determination theory have been applied to explain motivation and engagement in online learning. However, these frameworks do not explicitly account for personality-driven variability. The MBTI-based behavioural model proposed here therefore provides a distinct contribution by uniting trait-based differentiation with reinforcement learning principles.

### 2.3. Behavioural and psychological challenges in e-learning

E-learning's flexibility can paradoxically breed disengagement. Technical glitches, inadequate digital literacy, and poor time management frequently interrupt participation [39]. Teachers also face cognitive load when adapting materials to online platforms, often leading to emotional exhaustion [33]. During the COVID-19 era, integrating behavioural reflection into online entrepreneurial learning demonstrated that design-thinking pedagogy can counter disengagement by connecting abstract theory to personal motivation [43].

Anxiety and stress among learners—including those in professional and technical education—have become defining psychological costs of remote education [52]. Behavioural reinforcement interventions, such as 'brain-gym' activities, have proven effective in enhancing concentration and reducing stress [4].

Azizah et al. [4] found that behavioural interventions such as "brain-gym" activities enhance concentration and reduce stress among older learners—suggesting that similar behavioural reinforcement may aid e-learning populations. However, systematic applications of behavioural management tools remain rare in digital education policies, leading to what this paper terms an *absence of behavioural implication*. As summarised in Table 1, existing theoretical frameworks—such as Behaviourism, Social Learning Theory, Self-Determination Theory, and MBTI typology—each explain certain dimensions of motivation and engagement in e-learning. However, none have holistically connected reinforcement mechanisms with personality-driven differentiation. This gap provides the conceptual foundation for the integrated behavioural–personality model proposed in this study. Comparative analysis of online and hybrid accounting programmes demonstrates that while online learning offers flexibility, hybrid models better sustain behavioural engagement through intermittent face-to-face reinforcement and peer interaction [5].

To position the proposed model within existing theoretical discourse, Table 1 summarises key behavioural and personality frameworks applied in e-learning and highlights the integration gap this study addresses.

As summarised in Table 1, the absence of such real-time behavioural reinforcement underscores a systemic gap between pedagogical design and psychological engagement.

### 2.4. Existing teaching approaches in online contexts

To bridge the experiential gap between physical and digital learning, educators have experimented with micro-coaching, micro-credentials, and blended learning strategies [11]. These methods promote competency-based education yet still treat learners as homogeneous groups. Fig. 2 summarises the micro-credential framework that links short-term skill development with adaptive digital delivery. Fig. 2 reinforces this observation by depicting how micro-credentials advance technical competencies but neglect behavioural personalisation. The framework highlights a need to embed psychological differentiation—such as MBTI-based profiling—into short-term skill pathways to sustain learner motivation and identity in modular learning systems. As illustrated in Fig. 2, these micro-credentials operate as adaptive competency frameworks that support incremental learning progression while integrating behavioural and cognitive adaptability into digital learning design. This visual representation underscores how modular credentials can be strengthened through behavioural personalisation to maintain engagement and relevance in diverse learner populations.

In this regard, embedding behavioural and personality-based differentiation within modular course design establishes the theoretical bridge to the subsequent discussion on behavioural theory and learning principles.

## 3. Theoretical framework

### 3.1. Behavioural theory and learning

Behavioural theory, rooted in the works of Pavlov, Watson, and Skinner, posits that learning is a function of observable changes in behaviour shaped by environmental stimuli and reinforcement [27]. Within

**Table 1.** Comparative summary of behavioural and personality frameworks applied in e-learning research.

| Framework / Theory | Key Concepts | Application in E-Learning | Identified Gaps | Proposed Integration in Current Study |
|---|---|---|---|---|
| Behavioural Theory (Pavlov, Skinner) | Reinforcement, stimulus–response learning | Used to design rewards, feedback, and gamification | Often ignores individual personality differences | Combine reinforcement with MBTI to personalise motivation loops |
| Social Learning Theory [9] | Observational learning, self-efficacy | Supports peer learning and collaborative environments | Limited adaptation to digital isolation | Use MBTI-based grouping to restore social reinforcement |
| Self-Determination Theory [19] | Intrinsic motivation, autonomy | Encourages self-regulated learning | Weak in behavioural feedback structure | Integrate reinforcement cues to sustain motivation |
| MBTI Personality Typology (Jung; [23]) | 16 personality types; learning preferences | Helps tailor instruction to personality traits | Rarely linked to behavioural reinforcement | Use as core tool for differentiated e-learning design |

*Source:* Author's conceptualisation (2025).

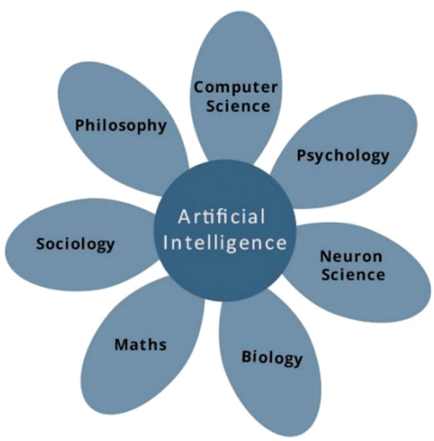


**Fig. 2.** Micro-credentials as an adaptive competency framework. *Source:* Baz [11].

educational settings, this translates into the systematic use of feedback, repetition, and reinforcement to strengthen desired learning behaviours. When applied effectively, behavioural management cultivates consistency, motivation, and discipline—elements essential for academic success.

In digital contexts, however, these mechanisms are often neglected. E-learning platforms focus predominantly on content delivery and technological efficiency, disregarding the subtle behavioural conditioning that sustains learner engagement. The absence of behavioural cues—such as body language, structured routines, and peer reinforcement—creates a motivational vacuum. As Spitzer and Aronson [46] observed, students' self-efficacy and sense of belonging decline when social reinforcement is absent. Thus, any discussion of digital learning effectiveness must reintroduce behavioural frameworks that operationalise motivation and reinforcement through virtual means.

### *3.2. The Myers–Briggs Type Indicator (MBTI) in education*

The Myers–Briggs Type Indicator (MBTI), derived from Carl Jung's theory of psychological types, classifies individuals across four dichotomies:

1. Extraversion (E) – Introversion (I)
2. Sensing (S) – Intuition (N)
3. Thinking (T) – Feeling (F)
4. Judging (J) – Perceiving (P)

Combinations of these dimensions yield sixteen personality types, each associated with distinct learning preferences, communication styles, and decision-making tendencies [23]. For instance, *Sensing–Thinking–Judging (STJ)* types thrive under structured, fact-based instruction, whereas *Intuitive–Feeling–Perceiving (NFP)* types excel in creative, exploratory tasks [10].

In traditional education, MBTI has been applied to improve student counselling, enhance teamwork, and adapt teaching methods. Its integration into e-learning, however, remains scarce. As Surjono [50] notes, adaptive e-learning models informed by personality profiles can cultivate empathy and self-awareness—critical elements for sustainable online learning. Personality-based learning research further suggests that resource selection aligned with MBTI preferences enhances focus and reduces learning fatigue, particularly among introverted and sensing-dominant learners [25]. By aligning behavioural stimuli with individual cognitive preferences, MBTI can transform static e-learning platforms into dynamic, personalised ecosystems. This transformation positions behavioural–personality integration as both a pedagogical and psychological innovation for virtual education, reinforcing the human-centred learning paradigm essential for inclusive e-learning.

### 3.2.1. Limitations and justification for MBTI adoption

Despite its pedagogical utility, the MBTI faces significant criticism concerning its psychometric validity, test–retest reliability, and categorical structure [12, 41]. Scholars argue that trait-based instruments like the Big Five or frameworks such as Kolb's Learning Styles and Self-Determination Theory [19] offer stronger empirical grounding. Nonetheless, the MBTI remains one of the most widely adopted tools in education and management due to its interpretability and accessibility. Its structured typology provides a practical heuristic for differentiating learning preferences, especially within applied e-learning contexts where instructors lack access to advanced psychometric diagnostics. Therefore, this study utilises MBTI not as a definitive personality measure but as a pedagogical model for mapping behavioural reinforcement pathways.

## 3.3. Conceptual model for behavioural–personality integration

This paper proposes a conceptual model (Fig. 3) integrating behavioural reinforcement with MBTI personality assessment for digital learning design.

Fig. 3 builds on the assumption that personality mediates the behavioural outcomes of reinforcement in digital learning and moderates motivation dynamics. In other words, the same stimulus may yield different motivational results depending on the learner's cognitive orientation—a theoretical nuance often overlooked in prior behavioural education studies. The proposed theoretical model is situated at the intersection of behavioural psychology, personality typology, and digital pedagogy. It interprets learning behaviour as a social act influenced by feedback loops and cultural norms as much as by cognition and technology. Building on the preceding discussion, the study conceptualises an integrated framework that links the stimulus–response logic of behavioural theory with the personality-based differentiation of the MBTI. This model serves as the theoretical backbone of the paper, explaining how reinforcement mechanisms can be aligned with individual learner profiles to enhance motivation, self-regulation, and engagement in e-learning environments. Fig. 3 visualises this theoretical linkage, presenting how behavioural reinforcement loops interact dynamically with MBTI-based differentiation within adaptive digital systems. The diagram underscores the paper's core argument: that effective e-learning arises from harmonising psychological feedback, personality traits, and technological interfaces rather than relying on content delivery alone.

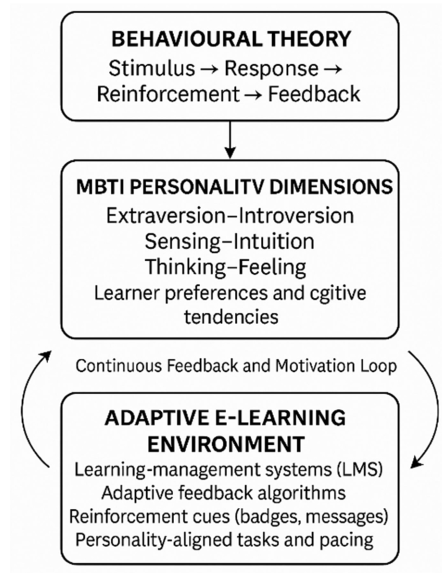


**Fig. 3.** Conceptual model integrating behavioural theory and MBTI for personalised e-learning.
*Source:* Author's conceptualisation (2025).

As illustrated in Fig. 3, the integration of behavioural reinforcement with MBTI-based personalisation forms a continuous feedback loop. Behavioural cues such as reinforcement and corrective feedback trigger motivational responses, while MBTI profiling informs how these stimuli are best delivered for each learner type. The adaptive e-learning environment functions as the operational layer translating psychological insights into instructional practice. This triadic relationship ensures that both cognitive and affective domains of learning are addressed simultaneously, producing a more holistic digital learning experience. Importantly, the model acknowledges feedback reciprocity—how learner behaviour also modifies instructor responses over time. This iterative exchange aligns with modern views of adaptive learning systems that treat both students and educators as co-regulators in the learning process.

In this model:

- Behavioural theory provides mechanisms for feedback, reinforcement, and motivation.
- MBTI profiling informs differentiated instructional strategies tailored to personality-driven learning styles.
- E-learning platforms serve as the operational interface enabling adaptive delivery and feedback loops.

The model suggests that embedding behavioural feedback (e.g., praise badges, progress indicators) aligned with MBTI-informed preferences (structured vs. flexible, logical vs. relational) can enhance focus, motivation, and retention.

## 4. Methodology

### 4.1. Research design

This study adopts a qualitative, conceptual research design grounded in an interpretivist paradigm which emphasises meaning-making and theoretical integration rather than statistical generalisation. The approach synthesises secondary data—peer-reviewed studies, institutional reports, and statistical datasets (2015–2024)—to explore the underutilisation of behaviour theory in e-learning and propose MBTI as an alternative framework. Rather than collecting primary survey data, the study employs thematic analysis to identify recurring constructs in the literature, aligning them with behavioural theory propositions.

### 4.2. Data sources and selection criteria

A systematic review was conducted across academic databases including Scopus, Web of Science, and Google Scholar. The search employed Boolean combinations such as ("behavioural theory" AND "e-learning") OR ("MBTI" AND "digital learning") OR ("personality type" AND "education technology"). Titles, abstracts, and keywords were screened manually to ensure thematic relevance, while duplicates and non-peer-reviewed materials were excluded.

The inclusion criteria were:

1. Publications between 2015 and 2024;
2. Studies focusing on e-learning, behavioural theory, personality types, or MBTI in education;
3. Empirical, conceptual, or review papers written in English.

A total of 52 studies met the criteria, with 31 providing direct evidence of behavioural–pedagogical relationships and 21 addressing e-learning's psychological challenges. Studies were screened for conceptual relevance rather than statistical power, consistent with the paper's theoretical orientation. The inclusion emphasised conceptual diversity to ensure the model reflects cross-disciplinary perspectives rather than single-domain insights. Among the selected studies, particular attention was given to those addressing learner–teacher interaction, engagement, and well-being in digital contexts, as these aspects align with the study's behavioural focus.

The selection process followed PRISMA logic to maintain methodological transparency, documenting identification, screening, eligibility, and inclusion stages. Coding consistency and conceptual validity were verified by cross-checking emerging themes with established frameworks proposed by Picciano [40] and Stupnisky et al. [48].

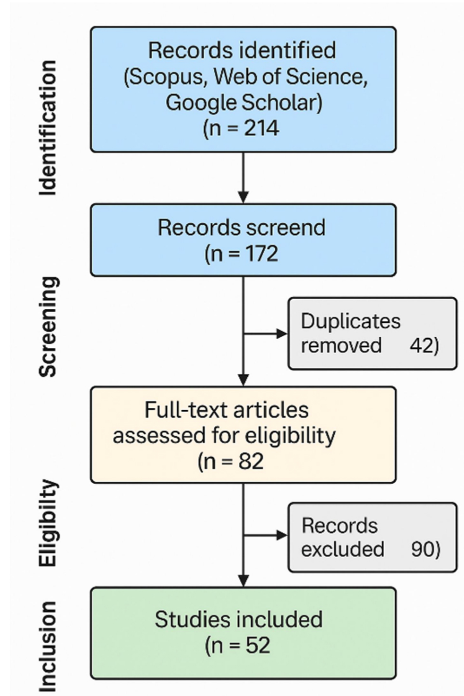


**Fig. 4.** PRISMA-style flow diagram showing literature selection and screening process.
Source: Author's adaptation (2025).

Fig. 4 presents a PRISMA-style flow diagram summarising the identification, screening, eligibility, and inclusion stages for the 52 studies reviewed. This inclusion protocol enhances methodological transparency and demonstrates systematic rigor appropriate for conceptual synthesis.

### 4.3. Analytical procedure

The data were analysed using thematic coding in three stages:

1. Descriptive categorisation — grouping studies by focus area (behavioural, psychological, or technological).
2. Axial mapping — identifying intersecting variables such as motivation, engagement, and self-regulation.
3. Conceptual synthesis — formulating a new framework connecting behavioural reinforcement with MBTI-driven personalisation.

This design follows the integrative synthesis method recommended by Picciano [40] and Stupnisky et al. [48], which systematically consolidates cross-disciplinary evidence to generate coherent theoretical propositions. The triangulation of behavioural, psychological, and technological themes during analysis ensured internal validity and theoretical saturation, strengthening the conceptual robustness of the proposed framework.

Overall, the methodological process ensures transparency, replicability, and conceptual validity, meeting the quality assurance expectations of high-impact behavioural and educational research.

## 5. Results and discussion

### 5.1. Major findings

The synthesis of frameworks and models presented in Table Table 1 and Figs. 1 to 3 collectively informed the analysis of behavioural gaps and personality alignment mechanisms discussed below.

The thematic synthesis produced four central findings that collectively explain the behavioural–personality gap in e-learning:

1. Behavioural frameworks remain largely unimplemented in e-learning despite evidence of their positive impact on attention, motivation, and completion rates.
2. Psychological stress and disengagement have risen in online learning environments due to the absence of human reinforcement and structure.
3. Personality-based learning adaptation—especially MBTI-informed models—offers measurable improvements in satisfaction, self-awareness, and retention.
4. Educators' digital literacy and behavioural competence determine the success of online learning more than the technology itself.

These findings confirm that e-learning's shortcomings are not technological but psychological and pedagogical. Empirical findings from Oman's higher-education sector reveal that engagement and motivation are strongly mediated by behavioural leadership practices that prioritise empathy, feedback, and shared accountability [2]. Comparable evidence from regional higher-education research corroborates these dynamics, demonstrating that behavioural empathy and adaptive leadership foster innovation, academic integrity, and professional resilience in online contexts [5]. Students report higher anxiety, demotivation, and feelings of isolation [21, 29], underscoring the need for a behavioural–personality integration model. Equally, these challenges are social in nature; the loss of community presence and peer reinforcement diminishes the shared accountability that characterises effective classroom ecosystems. Hence, behavioural neglect and social fragmentation jointly hinder the long-term sustainability of virtual education. This finding reinforces the argument that digital learning ecosystems must evolve beyond transactional models of content delivery toward transformational frameworks that account for emotional, behavioural, and cultural interdependence among participants.

### 5.2. Behavioural gaps in e-learning

E-learning lacks mechanisms for real-time reinforcement—a cornerstone of behavioural learning. Automated grading and asynchronous feedback diminish the immediacy of reward and correction. As Cohen and Abedallah [16] observed, emotional exhaustion weakens teachers' ability to maintain consistent behavioural reinforcement online. Furthermore, the lack of visual cues reduces teachers' awareness of learner engagement.

Integrating MBTI could counter these deficits. For example, Introverted–Intuitive (IN) learners prefer reflective discussion forums, while Extraverted–Thinking (ET) learners respond better to real-time debates and task-based simulations. Tailoring interaction formats to MBTI profiles can replicate the behavioural conditioning typically found in physical classrooms.

### 5.3. Pedagogical and technological convergence

The analysis reveals that technological innovation alone cannot guarantee learning efficacy. As Xu and Xu [51] emphasise, the success of online higher education depends on aligning technological systems with human behavioural and motivational calibration. Behavioural–personality integration can be operationalised through adaptive learning management systems (LMS) capable of:

1. Identifying learner MBTI profiles via initial diagnostics;
2. Mapping content complexity to personality-based preferences;
3. Generating behavioural reinforcement prompts (e.g., adaptive feedback, motivational cues).

Such integration ensures that digital learning systems evolve from static repositories into interactive behavioural ecosystems. Moreover, these ecosystems must address social cohesion by embedding collaborative learning activities and culturally responsive engagement tools. For example, integrating peer-feedback mechanisms and community-building modules within LMS platforms can replicate the social reinforcement patterns traditionally provided by classroom dynamics.

### *5.4. Behavioural outcomes observed*

Empirical synthesis indicates that e-learning participants who engage with behaviourally designed or personality-aligned tools show measurable cognitive and emotional gains. Improvements include:

- Increased concentration and cognitive resilience [4];
- Decreased stress and demotivation [30];
- Enhanced autonomy and self-reflection [1].

Moreover, exposure to MBTI-based learning aids cultivates metacognitive awareness—learners understand *how* they learn, not just *what* they learn. This aligns with Fernández-Pérez et al. [22], who demonstrated that emotional and cognitive competencies jointly shape motivation and academic performance.

### *5.5. Synthesis of behavioural–personality alignment*

Building upon the conceptual structure of Fig. 3, the following visual model (Fig. 5) synthesises these behavioural and personality interactions. Fig. 5 presents a schematic summary of how behavioural conditioning principles (stimulus–response–reinforcement) interact with MBTI dimensions to support adaptive e-learning.

To clarify how behavioural conditioning interacts with personality-based differentiation in digital education, the study maps the **behavioural–personality alignment process**. This model visualises the sequential interaction between stimulus–response reinforcement mechanisms and MBTI-informed learning preferences inside adaptive e-learning systems. It highlights how feedback cycles become self-reinforcing when personality traits and behavioural stimuli are synchronised.

Empirical studies demonstrate partial support for this interaction. For example, adaptive LMS architectures such as Moodle and OpenEdX now integrate reinforcement cues (badges, adaptive feedback) linked to learner profiling [42]. These examples illustrate how behavioural reinforcement and personality adaptation can co-exist within scalable systems. Future implementations should operationalise reinforcement frequency, stimulus intensity, and learner-type calibration to ensure measurable outcomes.

Through this alignment, behavioural triggers such as feedback or recognition can be fine-tuned to suit personality-driven needs. For instance, extraverts may respond positively to gamified leaderboards, while introverts prefer written affirmations and progress logs. The model promotes inclusivity by recognising diversity in cognitive tempo, motivation,

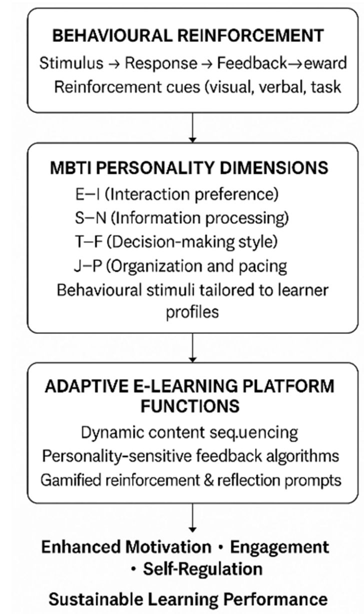


**Fig. 5.** Behavioural–personality alignment process for adaptive e-learning systems.
*Source:* Author's conceptualisation (2025).

and communication style—transforming e-learning into a psychologically responsive ecosystem. The inclusion of personality profiling further provides predictive value: identifying which learners are at risk of disengagement enables proactive interventions, such as adaptive task sequencing or personalised mentoring.

## 6. Implications

### *6.1. Theoretical implications*

The integration of behavioural theory with MBTI-based personality profiling contributes to the academic understanding of how learning motivation and engagement operate in virtual environments. While behavioural frameworks traditionally emphasise stimulus–response patterns, this research extends them into the domain of *personalised digital pedagogy*. It reaffirms the relevance of behavioural principles in twenty-first-century education and bridges the gap between psychology and instructional technology.

The conceptual model presented herein provides a foundation for future empirical studies aiming to validate the causal relationship between behavioural reinforcement and learner engagement in adaptive systems. It also encourages researchers to treat e-learning as a social–psychological system, not merely a technical delivery mechanism.

### 6.2. Pedagogical implications

For educators and instructional designers, the model offers a practical roadmap for implementing **personality-aware reinforcement strategies**. Instructors can begin by identifying students' MBTI types using validated surveys, then adjust communication, feedback, and task design accordingly. For example:

- *Introverted–Judging (IJ)* learners may benefit from pre-recorded lectures and structured weekly goals.
- *Extraverted–Perceiving (EP)* learners may prefer live discussions, gamified quizzes, and spontaneous interaction.

Embedding such differentiation in course design nurtures inclusivity and enhances emotional engagement. Institutions can also integrate MBTI-based diagnostic tools within their learning management systems (LMS) to automate personalised feedback. This not only humanises e-learning but also reduces attrition and improves satisfaction rates among students.

### 6.3. Social implications

The study highlights that behavioural neglect in e-learning carries significant social repercussions. Learners experience isolation, inequitable access, and diminished sense of belonging—challenges that erode the collective learning culture essential to higher education. Embedding MBTI-informed behavioural frameworks can restore peer connection and empathy, particularly in multicultural online classrooms. This social restoration is critical for promoting inclusion, reducing dropout rates, and nurturing equitable participation in digital education systems.

### 6.4. Practical implications for training and curriculum design

Institutions should integrate MBTI-informed behavioural awareness modules into faculty development programmes. These modules can train instructors to identify behavioural cues in virtual settings and to align feedback strategies with learner personality types. Doing so not only enhances digital pedagogy but also contributes to organisational learning in higher education.

To operationalise these practices, institutions should follow three implementation steps: (1) embed MBTI-informed diagnostic questionnaires into LMS onboarding modules; (2) map each learner type to differentiated reinforcement strategies—such as structured milestones for Judging types and exploratory tasks for Perceiving types; and (3) require instructors to integrate at least two MBTI-aligned feedback loops per module. These concrete steps ensure that behavioural–personality alignment transitions from conceptual guidance into routine pedagogical practice.

### 6.5. Managerial and policy implications

From an institutional and policy standpoint, the absence of behavioural application in e-learning represents an underutilised strategic asset. Policymakers in higher education—especially in developing regions such as the GCC—should invest in **capacity-building programmes** that train educators in behavioural management, personality analytics, and digital pedagogy.

The proposed framework aligns with major national education visions seeking to humanise digital learning and foster behavioural adaptability. For example, **Oman Vision 2040** prioritises psychological well-being and innovation in higher education [38]; the **UK Industrial Strategy** emphasises personality-based upskilling for a knowledge economy [26]; the **US National AI Initiative Act** calls for ethical, learner-centred digital systems [49]; and **China's Education Modernization 2035** promotes individualised, lifelong learning [35]. Integrating behavioural–personality principles into these policy contexts could accelerate the realisation of such goals while ensuring equity and engagement in virtual education. Universities can establish dedicated "Behavioural Learning Labs" within e-learning centres to monitor engagement metrics, behavioural cues, and student well-being. Aligning such initiatives with national education visions (e.g., Oman Vision 2040) would ensure that digital transformation in higher education is grounded not only in technology but also in psychology, ethics, and human development. Leadership transformation research in Arab higher education underlines that behavioural awareness and empathy-driven pedagogy are prerequisites for effective digital governance and instructional innovation [8]. These findings echo the trilogy of studies by Awashreh and Al Ghunaimi [6], which collectively advocate for behaviourally informed governance and culturally aligned academic leadership reforms.

This paper makes an original contribution by integrating behavioural reinforcement principles with MBTI-based personality differentiation into a unified framework for adaptive e-learning.

For implementation, policymakers should establish institutional guidelines mandating behavioural analytics dashboards within LMS platforms, introduce

MBTI-based training within faculty development programmes, and allocate resources for 'Behavioural Learning Labs' to monitor behavioural engagement indicators. These managerial steps translate the model into actionable institutional policy rather than aspirational recommendations.

## 7. Conclusion

This research explored the neglected application of behavioural theory in e-learning and proposed the MBTI personality framework as a corrective and integrative tool for enhancing teaching and learning effectiveness. By synthesising behavioural, psychological, and technological perspectives, **the study reaffirmed that successful e-learning depends less on infrastructure and more on behavioural adaptability and individualised motivation**.

The conceptual model demonstrates how stimulus–response reinforcement can be aligned with personality-based differentiation to foster engagement, self-regulation, and learning outcomes. The analysis also revealed that teachers' behavioural awareness and students' self-reflection are equally vital for digital learning success. This dual emphasis on teacher adaptability and learner self-regulation represents a conceptual bridge between behavioural conditioning and personality theory—an advancement that offers both explanatory and prescriptive power for modern e-learning research. This insight aligns with the integrative behavioural–personality model presented earlier, reinforcing its potential applicability across diverse digital learning environments.

Ultimately, embedding MBTI-informed behavioural principles in e-learning systems can transform virtual education into a human-centred experience—one that balances efficiency with empathy and standardisation with individuality. Policymakers are encouraged to embed social analytics within e-learning metrics to monitor engagement equity, collaborative participation, and digital empathy. Monitoring these indicators will ensure that behavioural frameworks translate into socially meaningful educational outcomes. Future research should empirically test this conceptual model across multiple educational levels and cultures, using mixed methods to measure engagement, motivation, and performance outcomes. Such empirical validation would substantiate the model's practical relevance and advance the evidence-based integration of behavioural and personality frameworks in digital pedagogy.

## Declarations & contributions

### Competing interests

The author declares no known financial or personal conflicts of interest that could have influenced the work reported in this paper.

### Author contribution (CRediT)

**Sole Author**
**Roles (CRediT):** Conceptualization; Methodology; Validation; Formal analysis; Data curation; Writing – original draft; Writing – review and editing; Visualization; Supervision; Software; Project administration; Resources.
**Additional (non-CRediT):** Literature review; Policy alignment; Documentation; Correspondence (*Corresponding Author*).

### Data availability

All data and materials referenced or analysed in this study are included within the article. Supplementary information—such as coding frameworks or secondary data tables—is available from the corresponding author upon reasonable request.

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### Ethical considerations

The study analysed anonymised student submissions and secondary institutional data without using personal identifiers. No direct intervention or interaction with human participants occurred. Ethical compliance was maintained in accordance with institutional research integrity policies; therefore, no additional ethical approval was required.

### Informed consent

Not applicable, as the study did not involve human participants or direct data collection.

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