Developing a Combined VARK and Social Condition Dominance Diagnostic to Optimise Student Learning Experiences

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ABSTRACT

Traditional higher education models frequently rely on a “one size fits all” approach to instructional delivery, which can lead to significant students’ learning difficulties and diminished motivation. While sensory preference models like Neil Fleming’s VARK (Visual, Auditory, Reading, Kinaesthetic) have been widely adopted to personalise learning, they often fail to account for the social conditions and environmental preferences under which information processing occurs. This action research study investigates the design, development, and empirical deployment of SoVARK. This novel digital diagnostic tool integrates VARK sensory modalities with social condition learning dominance to map student learning preferences. Deployed digitally to a cohort of undergraduate students (N = 123, unique respondents = 97), the diagnostic revealed a critical baseline of student needs: 74.8% of the cohort preferred processing information under Solo (47.2%) or Reflective (27.6%) conditions, with Visual-Solo (28.5%) emerging as the single most dominant combined learning profile. By mapping these multidimensional learning preferences, SoVARK provides immediate, automated, and personalised feedback through digital flipbooks containing a custom study strategy known as The Success Blueprint. This study demonstrates how low-cost, scalable digital diagnostics can be successfully developed and implemented to optimise student learning experiences, enhance self-directed learning, and provide concrete, verifiable evidence of educational innovation for academic promotion audits.

Keywords: VARK; Social Learning Styles; Personalised Learning; Digital Diagnostics; Educational Innovation.

INTRODUCTION

In contemporary higher education, a student’s struggle to master complex academic concepts is frequently misattributed to a deficit in cognitive ability, when the root issue is often that the instructional method does not align with the student’s learning mind (Katsaris & Vidakis, 2021; Nurasma’ Shamsuddin, 2020). Learning styles represent the diverse, individualised approaches, preferences, and strategies that students employ when acquiring, processing, and retaining new information (Norasmah Othman & Mohd Hasril Amiruddin, 2010). While recognising and accommodating this diversity has become a cornerstone of student-centred learning (Payaprom & Payaprom, 2020), a major gap persists in educational practice: traditional instructional preference models focus heavily on sensory pathways (visual, auditory, textual, or kinaesthetic) while overlooking the critical social environments or conditions in which learning takes place (El-Sabagh, 2021; Sim & Mohd Matore, 2022).

This discrepancy is particularly evident in contemporary university classrooms. Academic curricula have increasingly shifted toward active, collaborative, and socially engaging modalities, such as unstructured peer negotiations, group projects, and team-based debates (Hockings et al., 2018). Although peer interaction can promote academic development and foster collaborative professional identities (Dantas & Cunha, 2020), immersing students directly into these environments without a structured preliminary transition may prove highly counterproductive. Inadequate instructional designs that neglect individual learning styles have been demonstrated to adversely affect student behaviour, engagement, and overall academic performance (Anas et al., 2021; Shala et al., 2024).

Empirical evidence from our digital deployment of the SoVARK digital diagnostic tool reveals a stark pedagogical gap. Of the 123 active student submissions, 47.2% were classified as “Solo Learners” or “Independent Learners,” while 27.6% were identified as “Reflective Learners.” Taken together, 74.8% of the student population processes complex information best under quiet, solitary, or self-reflective conditions. Pushing these students directly into high-intensity, unstructured group negotiations without prior individual processing time creates substantial cognitive friction and behavioural withdrawal, ultimately undermining academic success. To bridge this gap, this study focuses on the design, development, and empirical deployment of a combined sensory-social diagnostic tool to map and support student learning preferences. We address two critical research questions:

RQ1: What are the dominant sensory (VARK) and social condition learning styles of undergraduate students?

RQ2: How does the development and design of a combined sensory-social diagnostic tool, SoVARK, support the personalisation of student learning experiences?

LITERATURE REVIEW

The Sensory Modalities of Information Processing: Fleming’s VARK Model

The concept of learning styles is established on the premise that individuals differ significantly in how they perceive, organise, interact with, and respond to the learning environment (Dantas & Cunha, 2020; Norasmah Othman & Mohd Hasril Amiruddin, 2010). Among the various instructional preference models, the VARK framework developed by Neil Fleming in 1987 is widely recognised for its simplicity, efficacy, and dynamic utility across diverse educational settings (Norasmah Othman & Mohd Hasril Amiruddin, 2010; El-Saftawy et al., 2024). Fleming categorises sensory modalities into four primary channels through which individuals receive and process information, namely, Visual (V), Auditory (A), Read/Write (R), and Kinesthetic (K) (El-Sabagh, 2021). The following explains the VARK components:

- Visual (V) learners favour symbolic devices and pictorial information, organising their reasoning through diagrams, flowcharts, graphs, arrows, and hierarchies rather than written words (Norasmah Othman & Mohd Hasril Amiruddin, 2010; Rawat et al., 2023).
- Auditory (A) learners acquire knowledge best through verbal explanations, discussions, lectures, tutorials, and oral presentations where they can listen and engage in spoken dialogue (Norasmah Othman & Mohd Hasril Amiruddin, 2010; Chaudhry et al., 2020).
- Read/Write (R) learners display a strong preference for written words, textbooks, glossaries, lists, lecture notes, and text-based handouts (Rawat et al., 2023; El-Saftawy et al., 2024).
- Kinesthetic (K) learners require hands-on practice, experiential learning, and real-life concrete examples, internalising information through physical interaction, touch, demonstrations, and active simulation (Norasmah Othman & Mohd Hasril Amiruddin, 2010; Rawat et al., 2023).

According to Fleming, a learner can be unimodal, preferring a single sensory modality, or multimodal (bimodal, trimodal, or quadrimodal), utilising a combination of sensory channels to capture information (Norasmah Othman & Mohd Hasril Amiruddin, 2010; Rawat et al., 2023). Within multimodal learning, researchers distinguish between VARK1 learners, who contextually select the single best-suited mode to maximise efficiency, and VARK2 learners, who labour-intensively process and correlate information across all four modalities to gain the deepest possible cognitive insight (Rawat et al., 2023). In tertiary education settings, identifying these sensory preferences provides a valuable medium for self-knowledge, enhancing student motivation and academic interest (Norasmah Othman & Mohd Hasril Amiruddin, 2010). When educators align instructional delivery with students' sensory preferences, they can capture attention, increase learning satisfaction, and significantly improve academic performance (Siti Nur Aishah Mohd Noor & Mohd Khairul Amri Ramly, 2023).

The Environmental and Social Conditions of Learning

While the VARK model successfully identifies how students physically perceive information, it does not account for the social conditions that dictate where and with whom students learn best (Katsaris & Vidakis, 2021). Learning is a complex, multifactorial process that is heavily shaped by social-interactional and environmental variables (Dantas & Cunha, 2020). Educational psychology models, such as the Grasha-Riechmann Student Learning Style Scales (GRLSS), highlight that a student's relationship with peers and teachers plays an interactive role in academic achievement (Devi et al., 2026; Riechmann & Grasha, 1974).

Social learning styles classify students based on their preferred interactive environments (Devi et al., 2026). Among these, the independent (solo) learning style is characterised by students who prefer to work alone, take personal responsibility for their learning, and explore content autonomously (Devi et al., 2026; Riechmann & Grasha, 1974). In collectivist educational environments or highly structured systems, students may also exhibit dependent learning styles, relying heavily on instructor direction, clear guidelines, and teacher-led authorities to structure their tasks (Riechmann & Grasha, 1974). Additionally, student learning preferences are often shaped by their engagement with informal social networks and online environments, which can influence their environmental study habits. Conversely, collaborative and participant styles are characterised by students who thrive in peer group discussions, cooperative problem-solving, and shared classroom activities (Kenanoğlu & Kahyaoğlu, 2024; Rumiantsev et al., 2023).

David Kolb's Experiential Learning Theory (ELT) similarly demonstrates that learning preferences are not static traits but the result of continuous interactions between the individual and their environment (Dantas & Cunha, 2020). For instance, Kolb's Assimilating profile aligns with a preference for visual and mental stimuli combined with solitary reflection and analysis. In contrast, the Diverging profile relies on concrete situations paired with highly social group work, verbal discussions, and constant feedback (Dantas & Cunha, 2020). Ultimately, forcing students into learning environments that conflict with their social preferences can lead to extreme academic frustration, cognitive overload, and classroom disengagement (Katsaris & Vidakis, 2021). Therefore, to build a truly student-centred classroom, educators must understand the precise intersection of both sensory processing and social condition dominance.

The Cognitive Benefits of Personalisation and Adaptive Diagnostics

The established pedagogical paradigm of "one size fits all" has increasingly faded in the face of modern educational technology and personalised learning solutions (Katsaris & Vidakis, 2021). Research consistently shows that personalised learning systems that adapt to individual learning styles drastically reduce learning time, elevate academic motivation, and improve student achievement (El-Sabagh, 2021; Katsaris & Vidakis, 2021).

However, a persistent operational challenge in traditional learning environments is the difficulty of accurately diagnosing and continuously updating student profiles (Katsaris & Vidakis, 2021). Traditional, long-form diagnostic questionnaires often suffer from low student compliance, as students become fatigued by excessive questions, leading to inaccurate profiles (Katsaris & Vidakis, 2021; El-Sabagh, 2021). According to El-Sabagh (2021), developing a low-barrier, automated digital diagnostics addresses this issue by providing instantaneous, visually engaging, and actionable feedback.

When students gain immediate metacognitive awareness of their combined sensory and social learning preferences, they can proactively realign their study habits, select optimal study environments, and experience a significant boost in self-efficacy (El-Sabagh, 2021; Katsaris & Vidakis, 2021). Furthermore, integrating such diagnostics provides academic institutions and instructors with a systematic, data-driven framework for designing targeted classroom interventions and meeting institutional quality audits (El-Sabagh, 2021).

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METHODOLOGY AND SOFTWARE ARCHITECTURE

This study employs an Action Research (Plan-Act-Observe-Reflect) design to investigate student diagnostics (Sheridan et al., 2026). The primary technical intervention is the design, development, and deployment of SoVARK, an automated student profiling application. Architecturally, the system is designed to bypass the friction points of traditional long-form questionnaires, using three interconnected modules. The name SoVARK is a combination of "Social" (So) and the VARK sensory modalities.

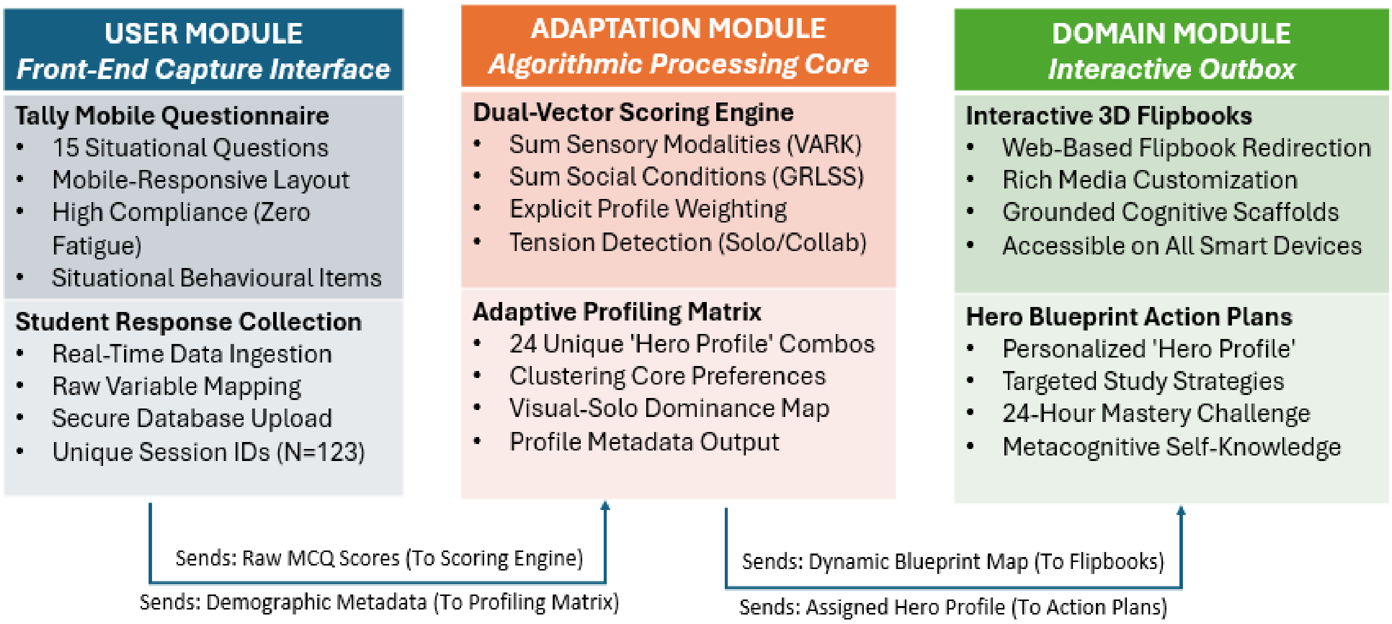

Figure 1 The Three-Module System Architecture of the SoVARK Diagnostic Platform

The technical implementation of the SoVARK diagnostic platform is structured around a three-module system architecture that captures, processes, and dynamically delivers personalised learning profiles without manual intervention, as shown in Figure 1. The first component, the User Module, serves as the front-end capture interface where students interact with a mobile-responsive Tally questionnaire. This module contains 15 situational behavioural questions meticulously designed to maintain high student compliance and eliminate diagnostic fatigue. Upon completion, the module handles real-time data ingestion, mapping raw multiple-choice responses and demographic metadata to unique session IDs before initiating a secure upload.

Once the data is ingested, the pipeline transitions to the Adaptation Module, which acts as the system's algorithmic processing core. Here, a dual-vector scoring engine concurrently aggregates sensory modality values (VARK) and social condition metrics (GRLSS), applies explicit profile weighting, and runs tension detection algorithms to assess solitary versus collaborative preferences. These calculated values are cross-referenced within an adaptive profiling matrix to map the student into one of 24 unique "Hero Profile" combinations based on core preference clustering. Finally, this resolved profile metadata is passed to the Domain Module (the interactive outbox), which automatically redirects the user to a web-based, rich-media 3D flipbook. This output provides grounded cognitive scaffolds, a personalised "Hero Blueprint" action plan with targeted study strategies, and a 24-hour mastery challenge to foster metacognitive self-knowledge across all smart devices.

The Three-Module System Architecture

a) The User Module

The journey begins entirely with the student. To bypass the diagnostic fatigue associated with traditional, long-form psychological tests (such as standard 60-item VARK or Grasha scales), students interact with a highly engaging, mobile-friendly questionnaire that takes only five minutes to complete (see Figure 2). This responsive interface captures their natural study habits under everyday academic scenarios rather than testing their academic competence.

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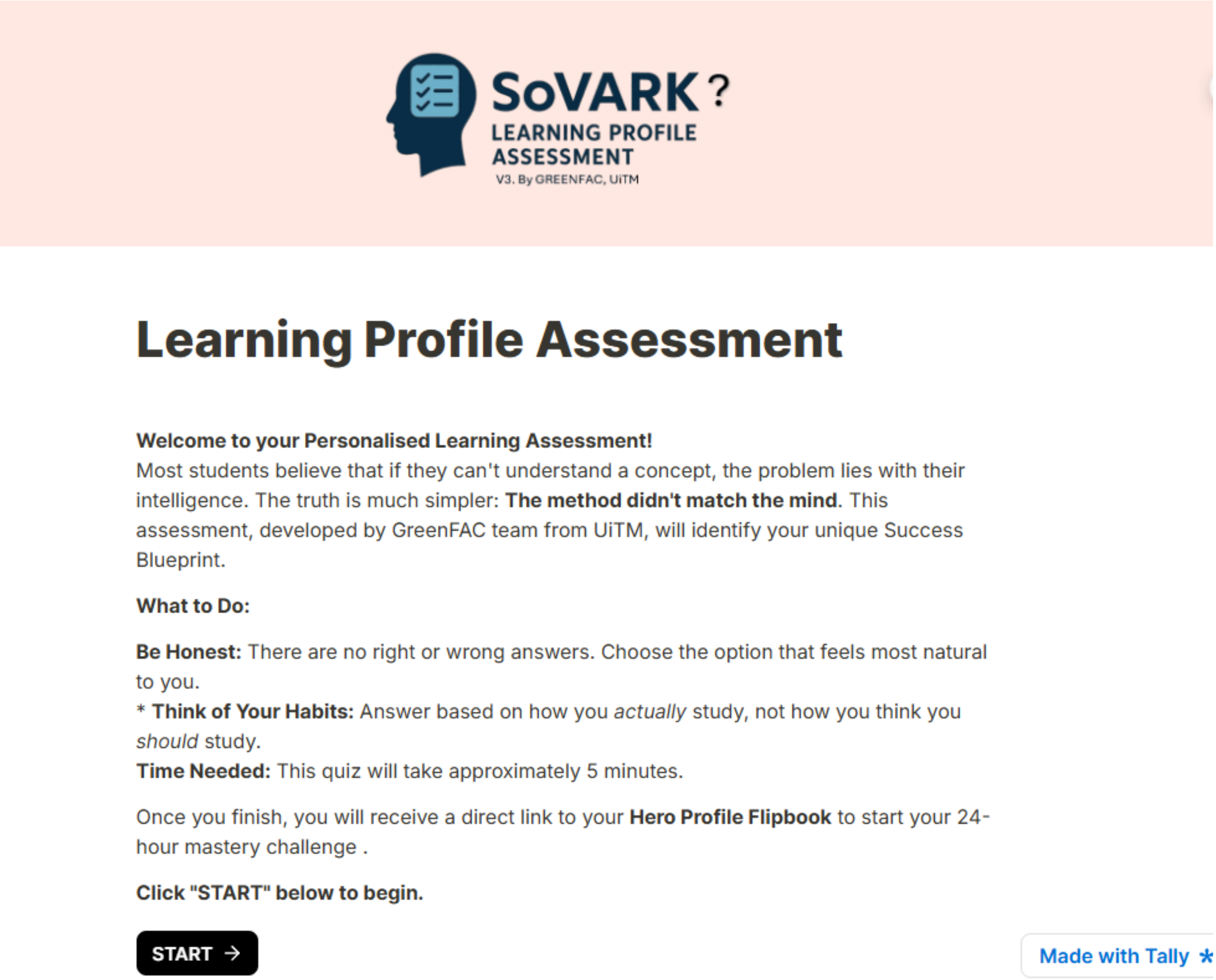

Figure 2 Mobile Assessment Interface

Rather than asking abstract questions (e.g., "*Do you like diagrams?")*, Each item presents a realistic, context-anchored scenario *(e.g., "You get a bad grade on a test. What is your first reaction?")*. Each question is mapped to a multi-option response matrix, where each choice simultaneously increments specific sensory (V, A, R, K) and social (Solo, Collab, Debate, Teaching, Competitive, Reflective) variables.

The front-end user interface and diagnostic instrument of the SoVARK platform were developed using Tally (Tally.so), a mobile-responsive, GDPR-compliant electronic form-builder. Tally's native form-calculator and conditional logic engine were leveraged to perform the real-time, concurrent scoring of the dual-vector diagnostic variables (sensory preference and social condition dominance) on a +1 basis without requiring external code execution during the user session.

b) The Adaptation Module

The moment the student clicks submit, the digital engine instantly takes over as the system's "brain". Without requiring any manual scoring or teacher intervention, the engine automatically analyses the student's habits along two parallel paths:

i) Sensory Preferences: It identifies how the student physically absorbs information best. Whether through visual diagrams, auditory explanations, reading text, or kinesthetic practice.
ii) Social Conditions: It maps the exact environment where the student processes information most effectively, such as solo independent study, quiet reflection, or collaborative team interaction.

By crossing the student's dominant sensory pathway with their preferred social condition, the engine instantly matches them to one of 24 highly personalised "Hero Profiles" (such as *The Visual-Solo Hero* or *The Auditory-Reflective Hero*) as shown in Figure 3.

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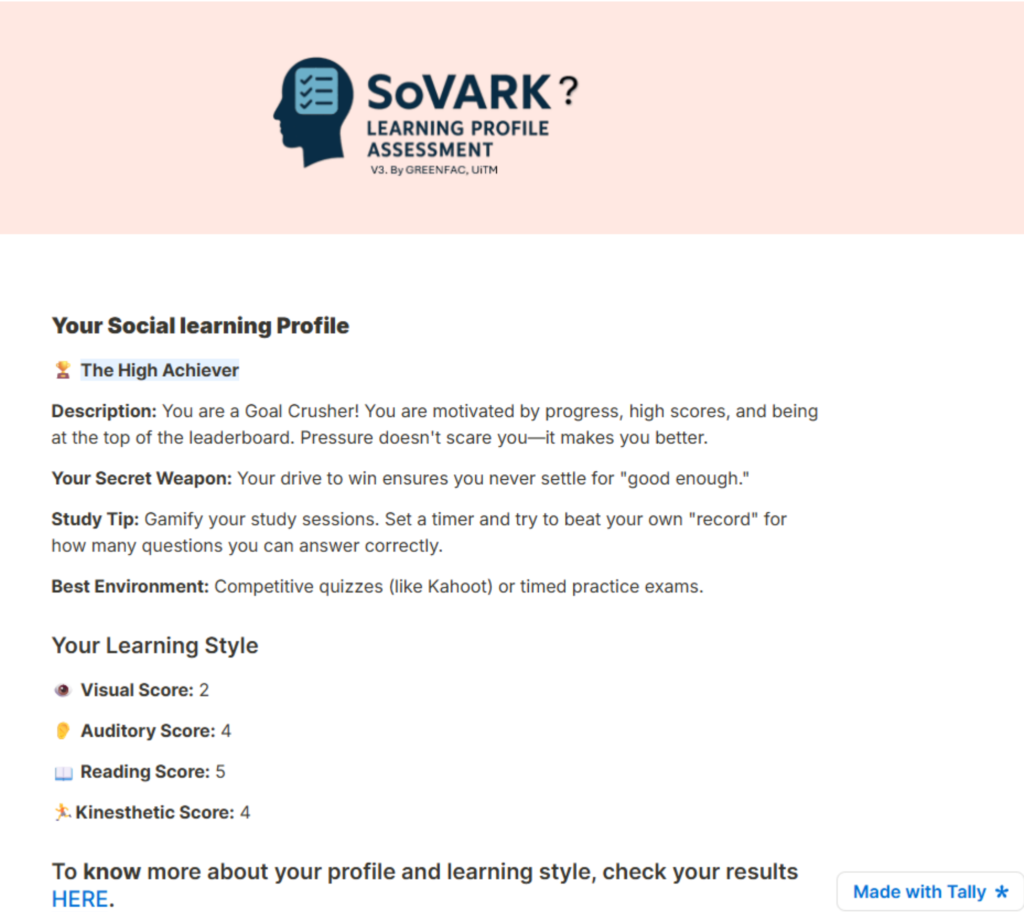

Figure 3 Personalised Success Blueprint interface

c) The Domain Module

Once the student's profile is assigned, the system automates the delivery of customised study solutions. Rather than subjecting the entire cohort to a rigid, "one-size-fits-all" curriculum, the system opens an interactive, 3D Online Flipbook designed specifically for their mind (see Figure 4). This booklet instantly provides the student with profile-specific study strategies. It launches their 24-hour mastery challenge, successfully proving that when a student struggles, it is not a deficit in intelligence but simply a mismatch in method. Upon profile resolution, the adaptation module initiates a backend integration with the Gemini Large Language Model API (developed by Google). Gemini acts as the cognitive translation layer, processing the resolved "Hero Profile" as metadata to dynamically compile, personalise, and structure the pedagogical advice before rendering the final interactive 3D Online Flipbook.

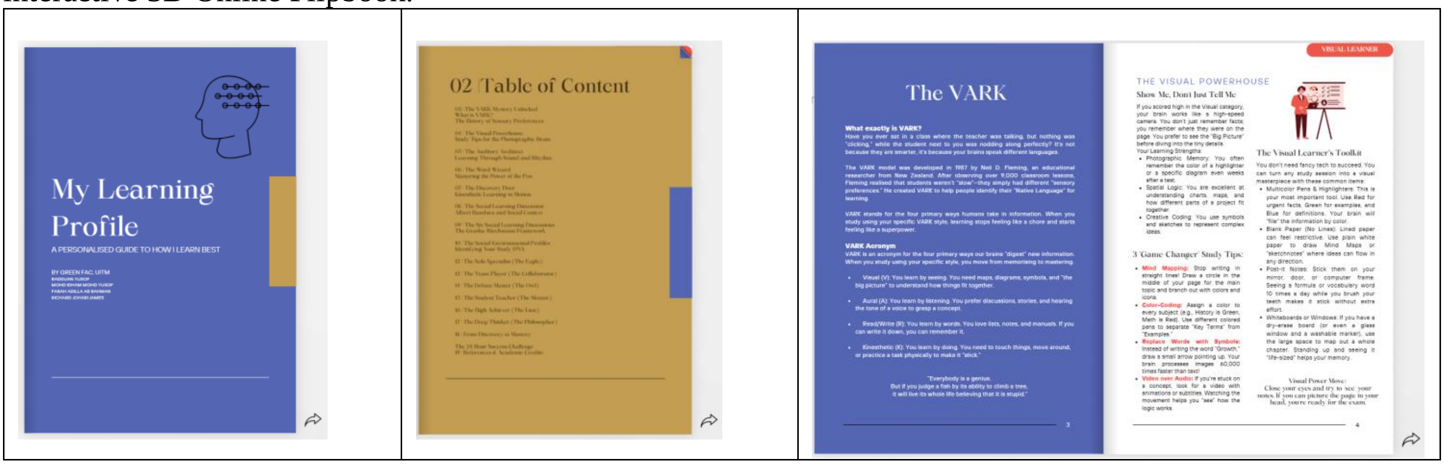

Figure 4 Personalised Flipbook Interface

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Tally Scoring Logic and Hero Profile Assignment

The Tally form utilises a dual-vector scoring matrix where each of the 15 situational items simultaneously increments both a sensory parameter (V, A, R, K) and a social parameter (Solo, Collab, Debate, Teaching, Competitive, Reflective) on a direct +1 basis (see Figure 5).

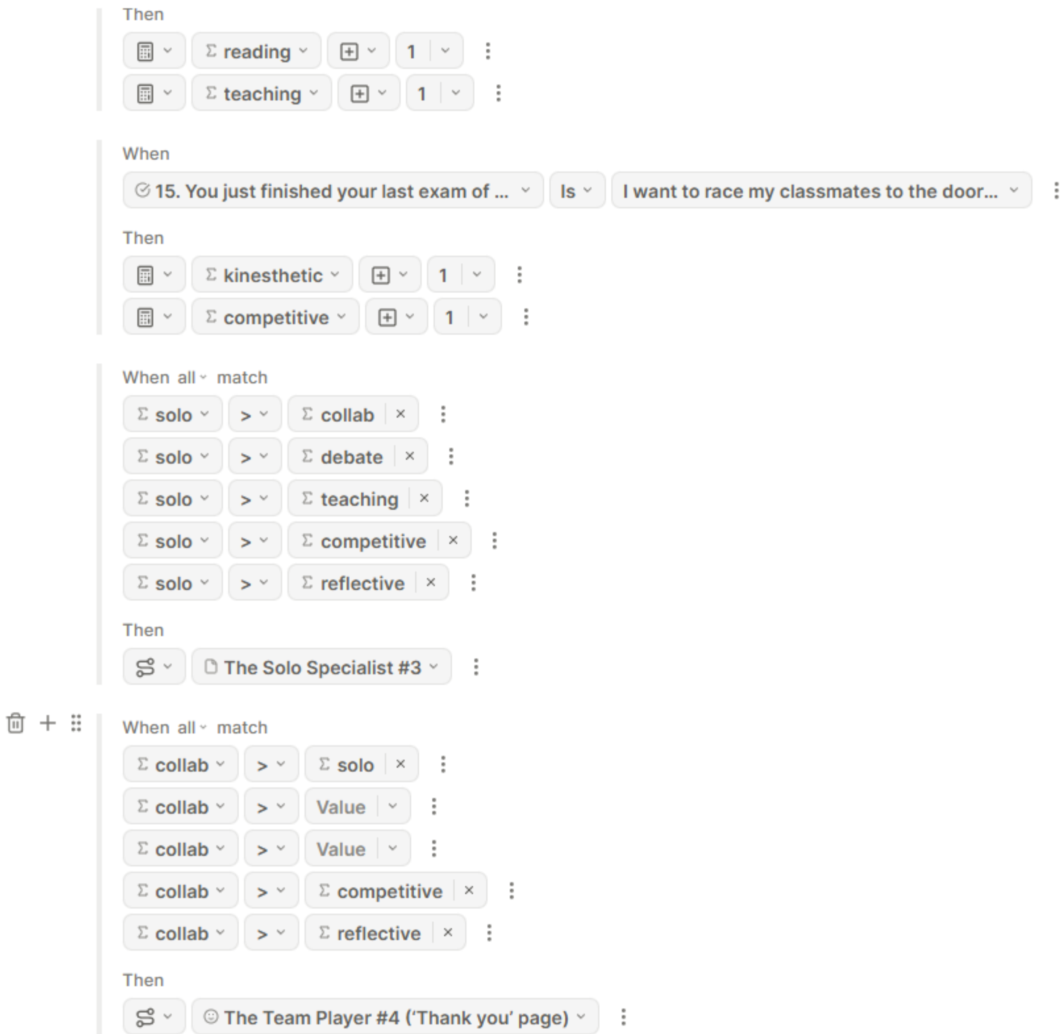

Figure 5 Tally Logic Mapping

For example, when answering Question 1 ("*You have a big test coming up. What is the very first thing you do?*"):

- Selecting option A ("*I use colourful pens to organise my notes by myself*") concurrently fires two scoring rules: visual is incremented by 1, and solo is incremented by 1.
- Selecting option B ("*Call a friend to talk about the test*") increments auditory by 1, and collab by 1.
- Selecting option C ("*I race against the clock to read the textbook as fast as I can*") increments reading by 1 and competitiveness by 1.
- Selecting option D ("*I walk around my room and think deeply about the topic*") increments kinaesthetic by 1, and reflective by 1.

Once the student completes all 15 items, the Adaptation Module compares the six accumulated social-condition vectors to determine the student's dominant environmental style. Using a series of hierarchical conditional checks (such as When solo > collab and solo > debate), Tally assigns the corresponding Hero Label:

- **The Solo Specialist** (Solo Dominant): Concentrates intensely without peer distraction; thrives in quiet "Study Sanctuaries."
- **The Team Player** (Collaborative Dominant): Recharges with high "social battery" interaction; thrives in active group discussions.

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- **The Debate Master** (Debate Dominant): A critical thinker who learns by testing arguments and finding logical contradictions.
- **The Student Teacher** (Teaching Dominant): Internalises knowledge by explaining concepts out loud to an audience.
- **The High Achiever** (Competitive Dominant): Highly motivated by milestones, progress tracking, and gamified challenges.
- **The Deep Thinker** (Reflective Dominant): Inner explorer who processes concepts through quiet, reflective contemplation.

The system then crosses this dominant social profile with the dominant sensory preference (e.g., visual or auditory) to map the student into their final combined 24-profile Hero Matrix (e.g., *The Visual-Solo Hero*).

Research Design, Participants, and Data Collection

The digital diagnostic was deployed as a course-level intervention to undergraduate students at Universiti Teknologi MARA (UiTM), Malaysia. Data collection occurred over a single-semester period. A total of 123 submissions were recorded, representing 97 unique students (some students completed the diagnostic at multiple points in the semester to self-reflect on the evolution of their study habits). The raw database consists of individual scores for all 10 sensory and social dimensions, along with detailed situational selections from the 15-item user module.

RESULTS AND DATA ANALYSIS

Quantitative Profile of the Cohort (RO1)

Descriptive statistical analyses were executed on the dataset of 123 active student submissions. Descriptive measures, including means and standard deviations (SD), were calculated for all ten variables to identify the dominant learning tendencies within the cohort.

Table 1 Means and Standard Deviations for Sensory and Social Learning Dimensions (N = 123)

Dimension	Variable	Mean (M)	SD	Max	Min
Sensory (VARK)	Visual	4.99	3.23	15.00	0.00
	Auditory	4.42	2.61	15.00	0.00
	Reading / Writing	3.54	2.12	13.00	0.00
	Kinaesthetic	2.04	1.99	13.00	0.00
Social Condition	Solo (Independent)	3.46	1.63	7.00	0.00
	Reflective	3.49	1.42	7.00	0.00
	Collaborative	2.11	1.40	7.00	0.00
	Teaching	1.90	1.07	6.00	0.00
	Competitive	1.67	1.47	6.00	0.00
	Debate	1.37	1.01	4.00	0.00

Primary Dimension Distributions

A comparative analysis between the univariate distributions and absolute profile assignments reveals an important nuance within the cohort's social learning dynamics. As displayed in Table 1, the cumulative cohort mean score across all 15 situational items was slightly higher for the Reflective dimension (M = 3.49, SD = 1.42) than the Solo dimension (M = 3.46, SD = 1.63). However, when evaluating absolute peak dominance per student (Figure 6), the Solo category yielded the highest total frequency, with 47.2% of individual student profiles resolving explicitly as Solo-dominant compared to 27.6% for Reflective. This indicates that while the Solo learning style represents the single most frequent absolute peak preference among individual students, the tendency toward Reflective processing is more uniformly distributed as a strong secondary or co-dominant trait across the cumulative scores of the entire cohort.

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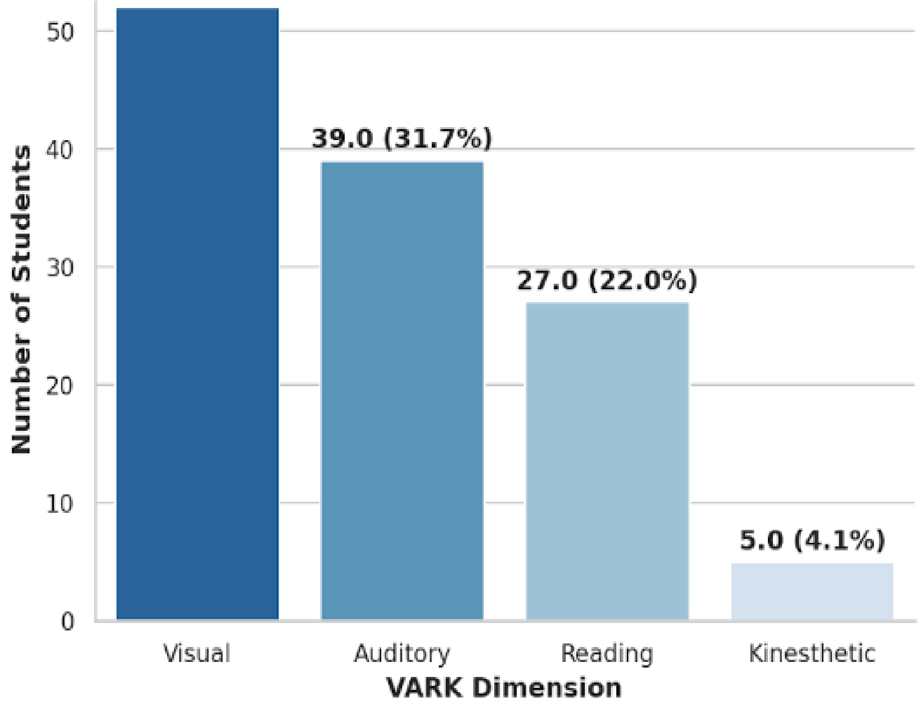

Figure 6 Primary Dimension Distributions (VARK Dimension)

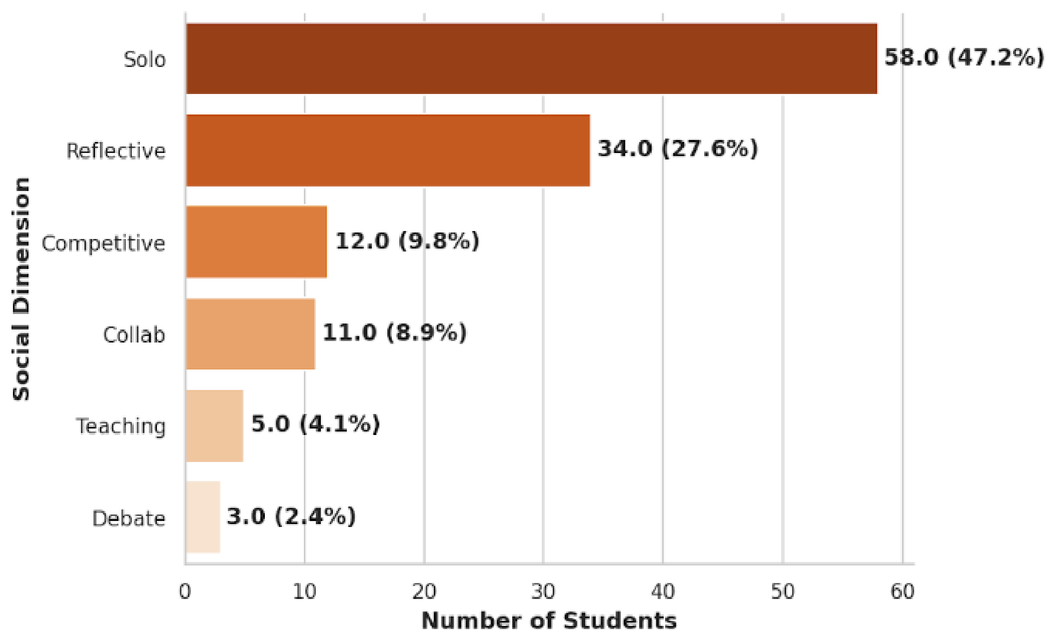

Figure 7 Primary Social Dimension Distributions

In the sensory domain, Visual (42.3%) and Auditory (31.7%) processing channels heavily dominate, whereas Kinaesthetic preferences represent a tiny minority (4.1%) (see Figure 6). In the social condition domain, Solo (47.2%) and Reflective (27.6%) styles represent the overwhelming majority, with 74.8% of the cohort preferring quiet, solitary, or highly reflective learning environments (see Figure 7).

Analysing the Multi-Dimensional Learning Preferences (RO2)

To resolve the complex intersections between student sensory modalities and their preferred environmental conditions, we executed a dual-vector cross-tabulation of the dominant scores. Rather than treating sensory perception (VARK) and social interaction style as independent variables, this multi-dimensional analysis maps the exact conditions under which a specific sensory channel is most effectively utilised.

Table 2 Top 10 Combined Multi-Dimensional Learning Profiles (N = 123)

Rank		Combined Profile	Count	Percentage (%)
1		Visual & Solo	35	28.5%
2		Auditory & Reflective	14	11.4%
3		Visual & Reflective	12	9.8%
4		Reading & Solo	12	9.8%
5		Auditory & Solo	9	7.3%
6		Auditory & Collaborative	8	6.5%
7		Reading & Reflective	7	5.7%
8		Auditory & Competitive	5	4.1%
9		Reading & Competitive	4	3.3%
10		Kinaesthetic & Competitive	2	1.6%

The Visual-Solo dimensional learning profile is the most dominant combined profile, accounting for 28.5% of the student cohort (n=35), as shown in Table 2. The resulting correlation matrix, illustrated in the correlation heatmap (see Figure 8), exposes a highly localised, high-density cluster that challenges traditional assumptions of student-centred learning. The heatmap reveals that the Visual-Solo combination is the most dominant profile. These students process information with high cognitive speed when presented with symbolic graphics, diagrams, and visual maps, but require quiet, independent study conditions to absorb and retain this knowledge.

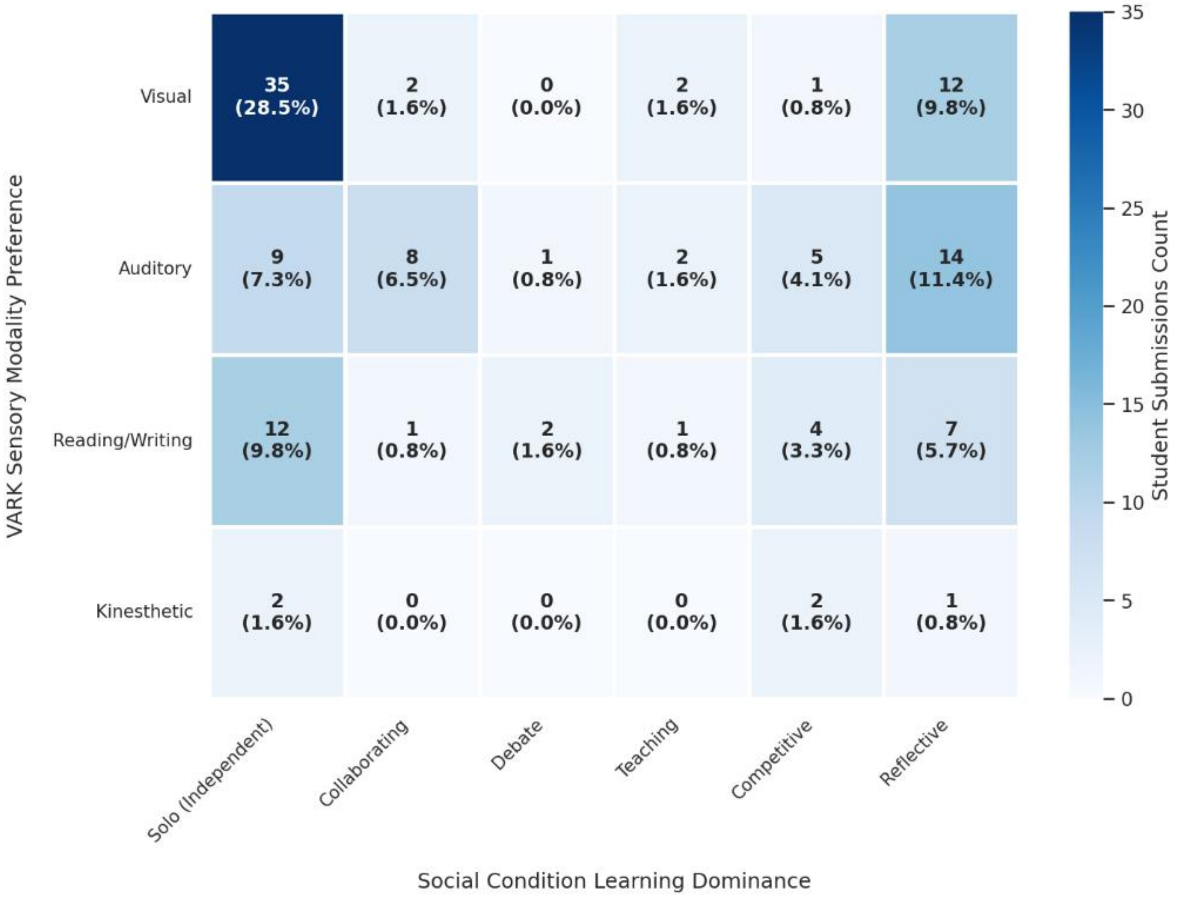

Figure 8 SoVARK Heatmap

Beyond this primary cluster, the data demonstrates a pronounced pull toward the “Solo” and “Reflective” domains across almost all sensory modalities:

- Auditory-Reflective learners represent the second largest segment at 11.4% (n=14), characterised by students who benefit from spoken explanations but require private, low-stimulus environments to reflect on and consolidate what they have heard.

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- Visual-Reflective and Reading-Solo profiles constitute parallel tertiary clusters, each representing 9.8% (n=12) of the cohort.

Synthesising these findings indicates a strong probability that 74.8% of the cohort processes information most effectively in solitary or highly reflective conditions, regardless of whether their primary perceptual channel is visual, auditory, or textual. Conversely, collaborative and active social domains represent a distinct minority in this student population, with Auditory-Collaborative (6.5%) and Kinesthetic-Competitive (1.6%) profiles appearing sparsely across the matrix.

This empirical concentration has profound implications for university instructional design. Higher education pedagogy increasingly mandates highly interactive, unstructured group tasks as the default vehicle for collaborative learning. However, the heatmap density indicates that pushing these solo-reflective minds directly into high-intensity, group-based negotiations without prior independent processing time creates severe cognitive friction.

By utilising a digital diagnostic pipeline, educators can map these multidimensional distributions in real time. This empirical mapping provides immediate justification for personalising study environments. Rather than forcing a uniform teaching style, the automated delivery of customised flipbooks empowers the dominant Visual-Solo (28.5%) and Auditory-Reflective (11.4%) cohorts to adapt their study spaces, minimise environmental distractions, and cultivate the exact metacognitive strategies necessary to excel academically.

On the other hand, it is also important to note that examining the full 4 x 6 matrix (visualised in the Heatmap, Figure 8) reveals that several combinations are entirely unpopulated in this student cohort. Specifically, Visual-Debate, Kinaesthetic-Collaborative, Kinaesthetic-Debate, and Kinaesthetic-Teaching are non-existent. This identifies clear empirical boundaries within the cohort’s learning behaviours. Kinaesthetic processing and verbal, high-intensity social environments (debate, collaborative, teaching) represent a stark mismatch for these students. Mapping these unpopulated intersections provides crucial evidence that certain modes of sensory perception naturally resist certain interactive conditions.

DISCUSSION

Personalisation and Metacognitive Awareness

The findings from the deployment of SoVARK demonstrate that traditional, undifferentiated higher-education classrooms introduce significant pedagogical friction (Katsaris & Vidakis, 2021). When academic programs enforce cooperative or highly collaborative group activities as the default learning method, they unknowingly create a hostile learning environment, especially for students who identify as Solo or Reflective learners (Riechmann & Grasha, 1974). On the other hand, behind the statistical "empty cells" of our diagnostic matrix lies a quiet, often overlooked struggle by another group of undergraduate students. The complete absence of profiles such as Kinesthetic-Debate and Kinesthetic-Collaborative represents a deep, systemic cognitive boundary. Kinesthetic learners process the world through physical presence, tangible touch, and focused execution (Fleming & Baume, 2006). When we force these hands-on learners into highly vocal, abstract, and socially intense debate or unstructured teamwork environments, we are not "challenging" them; instead, we are subjecting them to intense cognitive friction, which frequently leads to behavioural withdrawal, silent frustration, and academic disengagement.

As educators, we must express deep concern over how often our default instructional designs inadvertently penalise the very students who need tangible, grounded pathways to succeed. This pedagogical oversight is highlighted by Sheridan et al. (2026), who argue that successful reflective learning is a delicate, highly sensitive ecosystem that requires strict student safety, learner control over peer-group construction, and careful scaffolding. Pushing somatic learners into intense collaborative environments without these protective conditions forces them into anxious, perfunctory, or purely performative compliance rather than genuine critical reflection. Rather than expecting a single instructor to personalise classroom delivery into dozens of parallel paths, which is a logistical impossibility (Fleming & Mills, 1992), the SoVARK platform serves as a digital metacognitive mirror. Instead of uncritically applying uniform teaching methods that prioritise high-stimulus group activities over the diverse cognitive needs of our students (Dantas & Cunha, 2020), SoVARK helps students identify not only how they learn best but also which environments constitute negative friction zones that they should actively manage.

Consequently, the ultimate value of the SoVARK diagnostic framework extends beyond the simple technical validation of a novel profiling platform; it uncovers a profound operational misalignment in contemporary higher education design. Modern university curricula heavily privilege active, collaborative, and unstructured peer negotiations as the default gold standard for student engagement. However, our empirical findings reveal that this 'one-size-fits-all' mandate creates an adversarial ecosystem for the vast majority of the student body. Because 74.8% of the cohort processes complex academic information most effectively under Solo or Reflective conditions, forcing these students directly into high-stimulus, group-centric environments without preliminary individual processing time induces systemic cognitive friction and psychological withdrawal. Rather than fostering collaborative identities, over-indexing on uniform group tasks actively pushes three-quarters of the student population into preventable cognitive fatigue. By functioning as a metacognitive mirror, SoVARK provides empirical justification for a structural shift: instructional designers must treat solitary processing not as an outdated passive habit, but as a critical, high-efficiency cognitive prerequisite that must be structurally scaffolded prior to any social learning activities.

By utilising this combined diagnostic, institutions can move past this conflict and empower students to take control of their learning ecology. By allowing students to discover their profile, they gain instant metacognitive awareness (El-Sabagh, 2021). Rather than trying to force themselves to "match" every uniform classroom activity, the personalised flipbooks guide them to design their own study environments to minimise auditory distractions; whether they utilise coloured mind-mapping to structure complex policy issues, or engage in self-testing before participating in interactive classroom tasks (El-Sabagh, 2021). This self-directed realignment has been shown to drastically improve self-efficacy, reduce cognitive anxiety, and optimise student performance (El-Sabagh, 2021).

This concern becomes even more urgent when considering the broader generational shift characterising modern Gen Z cohorts. While contemporary educational policies heavily mandate constant, high-intensity collaborative tasks and group negotiations as the gold standard of learning, our empirical reality tells a very different, heartfelt story. An overwhelming 74.8% of our students quietly signal that they process complex information best under quiet conditions, Solo (47.2%) or Reflective (27.6%), matching the environmental preferences identified in classic socio-communicative frameworks (Grasha, 1996). Far from being a passive or anti-social posture, this autonomous stance is a highly active, self-regulating process. As Devi et al. (2026) demonstrate, independent learning is a critical metacognitive competence that fosters cognitive autonomy, resilience, and deep engagement, enabling students to digest and understand complex concepts on their own before seeking external assistance. Pushing these reflective minds repeatedly into unstructured group settings without providing them with vital "study sanctuaries" is a profound pedagogical misstep.

While collaborative interactions are undoubtedly valuable for professional development, Rumiantsev et al. (2023) caution that educators must intentionally balance structured peer cooperation with solitary, self-directed processing phases. Our students are exhausted; they are experiencing systemic "collaboration fatigue." We must listen to what our data is telling us about this generation. It is a call for us to stop over-indexing on loud classroom activities and start protecting the quiet, independent spaces where deep, authentic learning actually takes place.

Practical Implications and Institutional Adoption Strategy

Transitioning SoVARK from an isolated course-level diagnostic into a system-wide standard offers major practical benefits for modern higher education. The resolved sensory-social profiles can be integrated directly into learning management systems (LMS) as user-profile metadata. By utilising this standardised metadata, adaptive hypermedia engines can dynamically recommend profile-compliant study materials (such as interactive video-based concept maps for Visual-Solo students or audio summaries for Auditory-Reflective cohorts), enhancing self-directed study pathways without disrupting traditional lecture structures (El-Sabagh, 2021).

For educational administrators and curriculum designers, aggregating SoVARK databases provides clear, empirical evidence of cohort-wide learning profiles. Instead of relying on generalised pedagogical assumptions, administrators can audit course designs to ensure a healthy balance between solitary reflection phases and active collaboration requirements, actively preventing the systemic cognitive fatigue associated with over-indexing on uniform group tasks (Rumiantsev et al., 2023). The automated web-based architecture of SoVARK and the situational input-scoring flipbook offer a highly sustainable, zero-marginal-cost model for student-centred learning. Unlike traditional, labour-intensive interventions, this digital framework can scale across multiple departments or institutions, providing instantaneous, highly targeted metacognitive support to thousands of learners simultaneously (Katsaris & Vidakis, 2021).

Limitations and Future Research

While this study successfully demonstrates the high compliance and scalability of the SoVARK diagnostic, certain limitations warrant consideration. First, the empirical dataset is drawn from a single-cohort pilot, which may limit the generalisability of the student profile distributions to other demographic or cultural contexts. Second, while the diagnostic provides immediate metacognitive feedback via personalised flipbooks, this study does not measure the long-term impact of these flipbooks on students' GPAs across multiple academic semesters.

Future research should focus on integrating SoVARK across multiple faculties to analyse how learning profile dominance might vary across different fields of study (e.g., comparing social science students with STEM cohorts). Additionally, longitudinal studies that track academic performance metrics over two years would provide empirical validation of the long-term educational benefits of personalised learning profiles.

CONCLUSION

This study demonstrates that structural alignment strongly mediates the relationship between instructional delivery, individual learning preferences, and academic success. By designing and implementing SoVARK, we successfully developed a low-stakes, high-compliance digital diagnostic that bridges the gap between Neil Fleming's VARK sensory channels and the Grasha-Riechmann social learning conditions. The absolute dominance of the Visual-Solo profile (28.5%) and the collective concentration of Solo and Reflective preferences (74.8%) challenge the uncritical adoption of high-intensity collaborative modalities as universal pedagogical tools. Ignoring these socio-environmental baselines subjects the majority of students to intense cognitive fatigue and instructional friction.

By demonstrating how low-cost, automated digital diagnostics can scale seamlessly, the implementation of personalised flipbook interventions provides a practical model for balancing individual cognitive boundaries with the demands of institutional active learning. Ultimately, SoVARK proves that optimising the student learning experience requires moving past rigid collaborative dogmas and integrating data-driven, protective study environments that respect how the student mind actually operates. Systems-level integration of this tool into official university advising frameworks offers a tangible path forward for systematically improving student self-regulation and institutional support.

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