Who Thrives with AI? A Moderation Analysis of the Impact of AI-Based Learning on Students' Subjective Wellbeing by Learning Style

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Abstract—**This study investigates the impact of AI-based instruction on students' subjective well-being and whether individual learning styles moderate this impact. Grounded in Self-Determination Theory (SDT)—which emphasizes the basic psychological needs of autonomy, competence, and relatedness—and the VARK framework (Visual, Auditory, Read/Write, Kinesthetic), the research explores how AI-enhanced environments support wellbeing through learner-centered personalization. An experimental design was implemented with 465 high school students assigned to either AI-based instruction or traditional teaching methods. Subjective well-being was measured using a validated multidimensional scale aligned with SDT constructs. Moderation analysis revealed that while AI-based instruction significantly enhanced overall student well-being, the magnitude of the effect varied by learning style. Visual, Read/Write, Kinesthetic, and Multimodal learners reported higher well-being in the AI-based condition, whereas Auditory learners showed no statistically significant benefit. Kinesthetic and Multimodal learners experienced the most tremendous improvement, particularly in perceived competence and autonomy. These findings suggest that AI-based learning environments can promote student well-being when designed to fulfill basic psychological needs and align with individual learning preferences. The integration of SDT and VARK offers a novel framework for developing adaptive, human-centered AI systems that foster engagement and psychological well-being in educational settings.**

Keywords—Artificial Intelligence in Education, Student Subjective Wellbeing, Self-Determination Theory (SDT), Learning Styles, VARK, Adaptive Learning, Moderation Analysis.

I. INTRODUCTION

After COVID-19, educational institutions worldwide accelerated the use of artificial intelligence (AI) in the classroom to enhance remote and hybrid learning [1, 2]. AI-based learning platforms are part of the secondary learning landscape and can offer customizable content and intelligent tutoring on a scale [3]. The increase in AI-based learning is based on the increased awareness of the scale of opportunities AI presents: the global AI-in-education market is expected to be greater than $112 billion in 2034 [4]. A systematic review of AI in education reports that adaptive learning technologies have boosted test results by over 60% compared to traditional methods [5]. AI-based tutoring systems have also increased learning outcomes, on average by about 30%, and even in some cases reduced student anxiety by 20%, given the more responsive and more readily available support [6]. These results support AI's potential to improve academic performance and learners' experience of their emotions.

Nonetheless, in addition to the enthusiasm regarding the anticipated academic benefits [7], there is an urgent need to examine how AI-based instruction impacts students' subjective well-being; that is, students' measures of happiness, stress, and mental wellness in learning [8-10]. The recent pandemic has articulated awareness that success in education should include more than test scores, emphasizing student emotional health as a critical dimension [11]. There is increasing attention to student well-being as learning in schools potentially becomes more online and technology-mediated [12]. Stakeholders, including nations, provinces/territories, school districts, etc., have upheld that supporting positive emotions and well-being in students is a part of their healthy development. For example, the OECD [11] indicated that "children with positive emotions are more likely to grow into happy, confident, and healthy adults"; comparing those who would argue against this is hardly good science. However, literature focusing on AI in education has only begun to scratch the surface of these affective areas [13, 14]. In psychology and policy over the past two decades, interest in subjective well-being has increased, yet within formal education, considerably less attention has been paid to these dimensions [9]. In other words, while there will be one AI tutor or platform or another in secondary second schools faster than students can copy one another's coding, very little is known about whether children were happy learning from these tools and if they contributed to, or worse yet undermined students' emotional wellbeing in everyday learning [10, 12]. We do not want to be cavalier in suggesting that serious challenges to students' psychological well-being are arising. Still, it is perplexing because we know one could argue that AI-supported learning could support well-being, but the literature is far from an understanding of this [9]. A critical question thus emerges: How can we determine if AI-enabled learning environments support learning and positively support students' wellbeing?

Another critical issue often overlooked in previous studies is individual learner differences as a moderator of AI impact in educational contexts [15-17]. Education research has documented that a 'one-size-fits-all' methodology may not serve all students equitably [18]. This raises an interesting research question regarding AI learning: Who thrives with AI and why? We will look at learning style as one possible moderator, since students exhibit different preferences in consuming information. The widely used VARK classifications include Visual, Aural, Read/Write, and Kinesthetic [19, 20]. For example, some learners process the contents of visually-generated diagrams better, while others find listening to explanations more helpful, and still others prefer a hands-on process to learning [20, 21]. An example of a publicly available AI-based instruction system would offer learners content by utilizing commonly dominant modalities to deliver content (e.g., videos, live lessons, interactive exercises, etc.), which may not suit every learner's preferred learning modalities [22]. If the teaching modality of an AI system fits with a student's preferred learning style (more appropriately called a "learning modality"), that student may engage more, experience less frustration, and have more positive subjective well-being throughout the learning experience [23, 24]. If the modality does not fit a student's preferred learning style, that student might have less motivation or confidence in their learning [17, 21]. While this notion may be reasonably intuitive, it has yet to be explored empirically whether learning style (modality) moderates the relation between AI learning and subjective well-being [25]. Navigating this distinction is especially important for developing inclusivity in AI systems to benefit all learners [26].

Our research employs two related learning theoretical models to address these issues: Self-Determination Theory (SDT) [27] and VARK learning styles model [19, 20]. SDT focuses on the core psychological needs contributing to student motivation and well-being [27]. The theoretical premise of SDT is that students need to have the three core needs (i.e., autonomy, competence, relatedness) satisfied to foster learner engagement and well-being [27, 28]. An AI-enabled learning environment can help satisfy students' needs by allowing them to progress at their own pace, adapting to their level, and providing feedback and hints that might allow even a vague semblance of (social) presence [16, 29]. When students' three basic needs are met, they are inherently motivated and feel well-being in their educational contexts [27]. On the other hand, if the AI is stiff or isolating, it may frustrate basic needs (e.g., they may feel compelled to behave in specific ways, or feel alone in the AI-based learning situation), which will impact their well-being [28, 29]. VARK learning styles model identify the individual preference aspect-- learners differ in whether they enjoy or find learning activities anxiety-provoking, based on their preferred sensory modality [19, 20]. This, particularly differentiating between students' experience of learning based on learning style, allows for an examination of the aggregate supportive dimensions of AI-based learning (SDT) while considering the differences in the experiences students have as a function of their different learning styles [16]. Combining SDT and VARK perspectives is novel in the broader context of AI education research. It adds complexity to thinking about the 'beyond functional' aspects of technology-enhanced learning and how human psychology fits in [29].

This article notes a gap in the literature crossing the domains of AI-enabled learning, student wellbeing, and learner differences [9, 30]. While AI-enabled platforms in secondary schools appear to have strong potential to improve performance, we see a pressing need to assess whether AI-enabled learning platforms foster healthy educational experiences [13, 30]. Who Thrives with AI? We seek to answer this question by conducting a moderation analysis to investigate how AI-informed instruction impacts secondary students' subjective well-being, with learning styles (VARK) as the moderating variable [24, 31]. The study was implemented in live classrooms using an accessible AI learning platform, validating our findings. Our analysis considers subjective well-being (a conspicuous gap) rather than performance outcomes alone [30]. It is significant in light of calls for greater holistic review of educational technologies, including studying wellbeing more broadly [9]. By examining learning styles as a moderating variable, we also attempt to ascertain whether AI-influenced learning can support specific learner style profiles better than others, with implications for more personalized learning design [24, 31]. To the best of our knowledge, this is one of the first research studies in secondary education about how AI-based learning interventions affect student subjective wellbeing, and if they affect different learners differently [30]. As AI in schools is a new practice, we still need further research to better inform teachers and policymakers on effectively and equitably utilizing AI learning opportunities [13]. We add to a growing knowledge base to illustrate when AI-enabled learning is most beneficial and to which learners it benefits most. Our overall belief and thesis is that AI in education should now be informed not only by a desire for improved test scores and performance, but also by students' happiness, self-confidence, and overall sense of self-development. The findings from this study are intended to inform future designs for AI-enabled learning environments to enable all students to flourish academically and emotionally.

II. Methodology

A. *Research Design*

This study employed a quantitative, cross-sectional design to examine whether the impact of AI-based instruction on student subjective well-being differs across learning styles, as defined by the VARK model [32]. A moderation analysis framework was applied, using the PROCESS macro Model 1 [33] to test the interaction between AI-based instruction (independent variable) and learning style (moderator) in predicting student subjective well-being (dependent variable). This design is appropriate for assessing conditional effects and identifying whether specific learner characteristics amplify or attenuate the relationship between instructional modality and learner outcomes.

B. *Participants and Sampling*

The study sample comprised 465 secondary school students (grades 10–12) enrolled in multiple schools. A multistage cluster sampling strategy was employed to ensure the inclusion of students across different academic tracks, genders, and school types, thereby enhancing the representativeness and generalizability of the sample [34]. Depending on classroom implementation, participants were exposed to either AI-based instructional environments or traditional teacher-led instruction during the intervention phase. The final sample included a diverse range of students, with approximately equal representation across learning styles, as determined by the VARK questionnaire. The age of participants ranged from 15 to 18 years ($M = 16.4$, $SD = 0.87$), and the gender distribution was approximately balanced. Participation was voluntary, and ethical approval was obtained from the institutional review board of the affiliated university. Informed consent was secured from all participants and their legal guardians.

C. *Instruments*

Three main instruments were used in this study: (1) a student subjective wellbeing scale, (2) the VARK learning styles questionnaire, and (3) a binary variable to classify instructional method (AI-based vs. traditional).

1) *Student Subjective Wellbeing Scale*

Student Subjective Wellbeing was measured using a 16-item scale adapted from Renshaw et al. validated instrument [35]. This scale was selected due to its strong psychometric properties, precise alignment with educational contexts, and comprehensive measurement of students' subjective well-being within school environments. The adaptation process preserved the original dimensions of the SSWQ—namely, joy of learning, academic efficacy, educational engagement, and overall student subjective wellbeing—while slightly adjusting the wording to reflect the context of AI-based instruction in secondary education specifically.

2) Learning Style: VARK Questionnaire

Learning preferences were assessed using the VARK questionnaire (Version 7.8) developed by Fleming & Mills [19]. This instrument categorizes learners into four modal preferences: Visual, Auditory, Read/Write, and Kinesthetic. It includes 16 multiple-choice items, each allowing one or more responses. Scoring followed official VARK guidelines to determine each participant's dominant learning preference. Participants with equal or nearly equal scores in multiple categories were classified as Multimodal. The resulting learning style variable was treated as a categorical moderator in the analysis and dummy-coded for regression [36].

3) Instructional Method (AI vs. Traditional)

The independent variable, labeled Tool_Used, captured the type of instruction students received during the intervention. A value of 0 indicated traditional, teacher-led instruction without AI; a value of 1 indicated AI-based instruction featuring adaptive systems, automated feedback, and intelligent tutoring components. Assignments to instructional methods were based on classroom integration plans, not student choice. This variable was dummy-coded and entered into the moderation model as the predictor.

D. Procedure

The study was conducted over 30 weeks during the academic year 2024/2025 across multiple secondary schools. Before implementation, necessary permissions were obtained from the relevant educational authorities, school administrators, and the institutional ethics review board. Participating students and their guardians provided informed consent, and participation was voluntary and confidential. Depending on their classroom assignment, students were exposed to two instructional conditions: AI-based or traditional instruction. The assignment was determined based on the school's integration level of AI tools, which had been piloted in select classrooms as part of an educational innovation program. Efforts were made to match the two instructional conditions regarding content coverage and instructional time to reduce confounding variables.

In the AI-based instruction group, students engaged with digital learning environments that included adaptive pathways, automated feedback, real-time performance analytics, and interactive exercises. These systems were designed to adjust content difficulty and pacing based on each student's learning behavior. Teachers facilitated the learning experience but allowed the AI system to deliver the core instructional content. In the traditional instruction group, students received direct teacher-led instruction using conventional methods such as lectures, textbook-based activities, and paper-based exercises. These classrooms followed the same curriculum topics but did not use adaptive AI tools.

At the end of the instructional period, all participating students completed the VARK questionnaire to determine their dominant learning style and the student subjective wellbeing survey to evaluate their perceptions of the learning experience. Data were collected using online forms depending on the classroom context, and responses were anonymized before analysis.

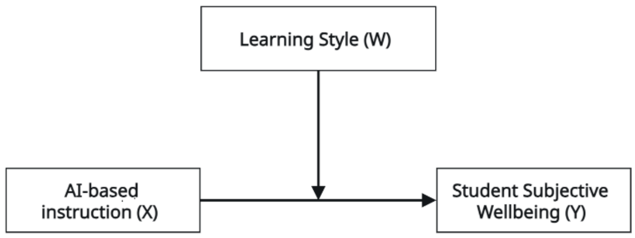
E. Data Analysis

All data were analyzed using IBM SPSS Statistics (Version 26), with moderation analysis conducted through the PROCESS macro (Version 5.0) developed by Hayes [33]. Descriptive statistics were first computed to examine all key variables' distribution, central tendency, and variability. Statistical assumptions checks were conducted to assess normality, linearity, homoscedasticity, and multicollinearity, and to screen for outliers and missing data [37]. Cases with excessive missing responses or extreme values were removed before analysis using listwise deletion [37].

The main hypothesis was tested using PROCESS Model 1, which evaluates the moderating effect of a single moderator on the relationship between an independent and dependent variable (See Figure 1). In this model:

- AI-based instruction (dummy coded: 0 = traditional, 1 = AI) was the independent variable (X)
- Student Subjective Wellbeing was the dependent variable (Y)
- Learning style, as classified by the VARK model, served as the categorical moderator (W)

Fig. 1. Proposed Model.



Learning style was dummy coded into four binary variables, with the Visual group used as the reference category. The model included the four dummy-coded learning style variables (Auditory, Read/Write, Kinesthetic, Multimodal) and their interaction terms with instructional condition (AI × Learning Style).

The conditional effects of AI-based instruction on student subjective well-being were estimated at each moderator level, allowing for the interpretation of how the relationship between instructional modality and student subjective well-being varied across different learning styles. A 95% confidence interval was used for all estimates, and significance was determined at $p < .05$.

III. RESULTS

A. Descriptive Statistics

Descriptive statistics were computed for all study variables. The overall sample included 465 secondary school students. Participants were classified into five learning styles using the VARK model: Visual (reference group), Auditory, Read/Write, Kinesthetic, and Multimodal. The distribution was as follows: Visual (n = 63, 13.5%), Auditory (n = 50, 10.7%), Read/Write (n = 74, 16.0%), Kinesthetic (n = 99, 21.3%), and Multimodal (n = 179, 38.5%). Student subjective well-being scores ranged from 1.00 to 5.00, with a mean of M = 3.68 and a standard deviation of SD = 0.76. Of the total sample, 234 students were exposed to AI-based instruction, while 231 received traditional instruction.

B. Moderation Analysis

A moderation analysis was conducted using the PROCESS macro (Model 1; Hayes, 2022) to examine whether the effect of AI-based instruction (Tool_Used) on student subjective well-being was moderated by learning style (VARK). Learning style was dummy-coded with Visual learners as the reference group, and interaction terms between Tool_Used and each learning style category were included in the model [36].

The overall model was statistically significant, $F(9, 455) = 12.40$, $p < .001$, explaining 20% of the variance in student subjective wellbeing ($R^2 = .20$). Importantly, the interaction between AI-based instruction and learning style accounted for a significant proportion of additional variance, $\Delta R^2 = .024$, $F(4, 455) = 3.34$, $p = .01$, indicating that the effect of AI-based instruction on student subjective wellbeing varied by learning style.

Table 1 presents the unstandardized coefficients for the complete moderation model. AI-based instruction positively and significantly affected student subjective wellbeing ($\beta = 0.40$, $p = .01$). Among learning styles, Kinesthetic learners reported significantly lower overall student subjective wellbeing ($\beta = -0.74$, $p = .02$) than Visual learners. No other main effects of learning style were statistically significant.

Although none of the AI × Learning Style interaction terms reached conventional levels of significance ($p < .05$), two interactions approached significance: AI × Kinesthetic ($\beta = 0.35$, $p = .07$) and AI × Multimodal ($\beta = 0.28$, $p = .10$), suggesting potential moderation effects for these groups (see Table 1 for complete coefficients).

TABLE I. MODERATED REGRESSION ANALYSIS PREDICTING STUDENT SUBJECTIVE WELLBEING FROM AI USE AND LEARNING STYLE

Predictor	Effect (β)	SE	t	p	LLCI	ULCI
Constant	2.86	0.24	11.75	.00	2.38	3.34
Tool Used (AI vs. Trad.)	0.40	0.15	2.69	.01	0.11	0.68
Auditory (W1)	0.28	0.33	0.87	.38	-0.35	0.92
Read/Write (W2)	0.06	0.36	0.16	.88	-0.66	0.77
Kinesthetic (W3)	-0.74	0.32	-2.30	.02	-1.38	-0.11
Multimodal (W4)	-0.47	0.28	-1.68	.09	-1.03	0.08
AI × Auditory (Int_1)	-0.19	0.19	-0.98	.33	-0.58	0.19
AI × Read/Write (Int_2)	-0.03	0.23	-0.12	.91	-0.47	0.42
AI × Kinesthetic (Int_3)	0.35	0.19	1.79	.07	-0.03	0.73
AI × Multimodal (Int_4)	0.28	0.17	1.64	.10	-0.06	0.62

Note: Visual is the reference group for learning style.

C. Conditional Effects of AI-Based Instruction by Learning Style

To explore the nature of the moderation effect, conditional effects of AI-based instruction on student subjective well-being were estimated at each level of learning style (Table 2). The effect of AI-based instruction was statistically significant for Visual ($\beta = 0.40$, $p = .01$), Read/Write ($\beta = 0.37$, $p = .03$), Kinesthetic ($\beta = 0.74$, $p < .001$), and Multimodal learners ($\beta = 0.68$, $p < .001$). The effect was positive but insignificant for Auditory learners ($\beta = 0.20$, $p = .13$).

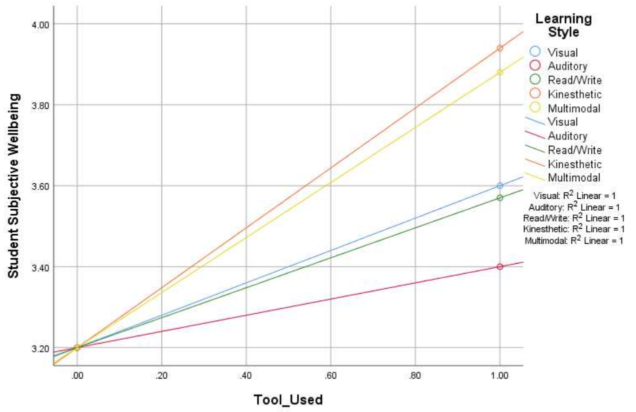
TABLE II. CONDITIONAL EFFECTS OF AI_USED AT EACH LEARNING STYLE

Learning Style	Effect (β)	SE	t	p	LLCI	ULCI
Visual	0.40	0.15	2.69	.01	0.11	0.68
Auditory	0.20	0.13	1.50	.13	-0.06	0.46
Read/Write	0.37	0.17	2.15	.03	0.03	0.71
Kinesthetic	0.74	0.13	5.88	.00	0.49	0.99
Multimodal	0.68	0.09	7.65	.00	0.50	0.85

Note. LLCI: β: Direct Effect. Lower-Level Confidence Interval. ULCI: Upper-Level Confidence Interval

These results suggest that kinesthetic and multimodal learners benefited the most from AI-based instruction regarding student subjective well-being, while auditory learners showed a weaker response. Figure 2 illustrates the interaction effect by plotting simple slopes of student subjective well-being across learning styles.

Fig. 2. Simple Slopes Plot of AI-Based Instruction Effects on Student Subjective Wellbeing by Learning Style.



IV. DISCUSSION

A. Interpretation of Findings in Light of SDT and Learning Styles

The current research supports the conclusion that AI-based instruction increased the students' subjective well-being compared to traditional instruction, aligning with recent findings in the literature [9, 30]. However, more importantly, this positive effect was tempered by learning style [24, 31]. In conjunction with SDT [27], the AI learning platform seemed to satisfy students' basic psychological needs - autonomy, competence, and relatedness - to a greater degree for most learner types [28, 29]. SDT suggests that greater autonomy, competence, and relatedness satisfaction lead students to benefit from greater intrinsic motivation and positive affect [27]. Consistent with this reasoning, Visual, Read/Write, Kinesthetic, and Multimodal learners indicated significantly higher well-being under AI instruction. It is our interpretation that the AI platform offered a more need-supportive learning environment for these students resulting in feelings of autonomy (self-paced, personalized learning), competence (adaptive feedback and challenges that could be achieved), and likely some form of relatedness (we are not sure of the source; the platform could have possibly offered encouragement or a sense of support, even when that support was virtual) [9, 29]. When satisfied, students grow in engagement and pleasure in learning and in intrinsic motivation, which likely explains the increased well-being we observed [27, 28].

From a learning styles (VARK) perspective, the benefits differed depending on how the AI platform complemented or improved one category of learning modalities [16, 19]. The VARK model delineates that learners can be categorized as Visual, Auditory, Reading/Writing, Kinesthetic, or in combinations [19]. The findings suggested that, in some ways, the AI-supported instruction was aligned with, or enhanced, Visual, Read/Write, Kinesthetic, and Multimodal learners [24]. For example, since Visual learners prefer information presented in a chart, diagram, or illustration format, the AI platform likely included rich visual content (e.g., infographics, videos), which may not be offered consistently in a traditional lecture format. Reading/Writing learners – those who learn best through text and writing – also thrived, presumably because the AI system involved significant on-screen text, hyperlinked resources, or writing-based interactions that align with their preferences [16]. The most significant gains were seen for kinesthetic and multimodal learners, a result that makes sense given the interactive possibilities of AI-based learning [24, 31]. Kinesthetic learners learn best by doing – whether with hands-on activities, experimentation, or simulations – and a structured classroom cannot continuously provide active learning and engagement. The AI platform is (hopefully) able to offer continuous or dynamic activities, simulations, or interactive opportunities to enable kinesthetic students to engage in "learning by doing" to increase their sense of efficacy and enjoyment [24]. Notably, e-learning environments can use scenario-based simulations to meet kinesthetic learners' needs, even replicating experiences that would be impractical in a real classroom [31]. Multimodal learners (those without a dominant style) showed the most significant benefit, which is plausible because an AI-based course simultaneously delivers content through multiple forms – text, visuals, and possibly interactive media – enabling these flexible learners to draw on all their strengths [20]. This finding aligns with previous research, indicating that learning interventions using multiple modalities resulted in better outcomes than single-mode learning approaches [16, 31]. In short, by affording most learners a chance to have more personalized and varied instruction that matched their learning modes, the AI condition also likely better supported students' basic psychological needs, compared to a traditional lesson that was standardized and less tailored [27, 29]. Collectively, these factors help explain higher subjective well-being overall.

However, one group – Auditory learners – did not experience a significant difference in well-being between the AI and traditional conditions. This null finding is noteworthy and highlights how learning style can influence the effectiveness of technology-based instruction [17, 19]. Auditory-preferring students typically "get a great deal out of lectures" and oral explanations, retaining information they hear and favoring spoken inputs (e.g., class discussions, podcasts) over written text [19, 20]. In a conventional classroom, such learners can learn through listening to the teacher talk and peer discussions. If the AI platform primarily delivered content via text and visuals (as many do), it may not have provided a substantially better auditory experience than the traditional setting [24]. In essence, auditory learners in the AI condition might have lost the familiar human voice and interactive discussion that they thrive on, without a sufficient replacement [9]. While the AI platform likely increased autonomy and provided instantaneous feedback (boosting competence) for all students, it may have inadvertently underserved the auditory modality and the sense of human connection [27, 29]. As a result, auditory learners' basic needs satisfaction, particularly the need for relatedness or engagement through communication, could have remained unchanged, leading to similar well-being levels across AI and non-AI settings [28]. This interpretation aligns with the idea that auditory learners are "pleased with embedded audio narration and lectures" in e-learning courses [17]. If such elements (e.g., voice-over explanations or conversational agents) were lacking or insufficient in the AI platform, auditory-oriented students would not reap additional benefits. It is also possible that auditory learners adapted equally well to both formats, experiencing neither a notable gain nor loss, perhaps because the traditional classroom already catered firmly to their preferred style (through spoken instruction) and the AI environment did not enhance that aspect further [19]. In future implementations, adding robust audio features or live voice interactions to the AI system might specifically elevate auditory learners' engagement and well-being [9, 29]. For now, the absence of improvement for this group serves as a reminder that technological innovations in education are not one-size-fits-all; when a learning tool excels in some modalities but not others, surely students may be left on an equal footing with (or even at a disadvantage to) traditional methods [31].

V. Implications

The results have significant implications for developing AI-based learning systems that are pedagogically useful and support students' well-being. First, the success of the AI platform in improving the well-being of the majority of students suggests that integrating SDT principles into educational technology, in a thoughtful way, can result in a great advantage [27, 29]. Environments that give learners more choice and control (supporting autonomy), adapt to their skill level with feedback and appropriate challenges (supporting competence), and potentially include social or collaborative elements (supporting relatedness) will likely foster happier, more motivated learners [28]. Researchers have emphasized the need to create educational technologies that actively satisfy these basic needs to improve student outcomes [9, 29]. Designers of AI learning platforms should therefore embed motivational supports – for example, offering meaningful choices in learning pathways, allowing self-pacing, personalizing feedback, and perhaps incorporating a virtual mentor or peer interaction forum to maintain a sense of connection [13, 14].

Secondly, the moderating role of learning style indicates that AI-based courses must be multimodal and inclusive by design [17, 24]. Given that the VARK framework and our findings indicate that students have preferences for how they learn, an effective AI system must be designed to accommodate various sensory modalities [19, 20]. The important takeaway from an instructional design perspective is that we need to provide students with content multiple ways and at the same time: plenty of pictorial representations for the visual learner; text and opportunity for note-taking for the read/write learner; audio narration or verbal explanations for the auditory learner; and the ability to do interactive and hands-on activities for the kinesthetic learner [31]. This will ensure that no group will be left out. In practice, this will mean providing text-based learning experiences with optional voice-over additions or problem demonstrations, videos or interactive diagrams, simulation-based exercises, or virtual lab experiences. The kinesthetic learner data reinforced the benefit of interactive elements, as they stood to benefit the most from the interactive aspects of the learning experience. As such, the simulated experiments, drag-and-drop problem-solving, or any other "learning by doing" features will be key in an AI learning environment [24]. Incorporating such features helps kinesthetic learners and can engage all students by making learning more active and authentic.

Likewise, to support auditory learners (the one group that did not thrive with the AI platform), developers should consider adding robust audio components: for instance, spoken explanations, conversational agents that can talk a student through a problem, or integration with class discussions via the platform [17]. Providing a social presence – whether through the teacher's involvement in the learning platform, peer collaboration tools, or an empathetic AI tutor persona - can also help strengthen the relatedness factor and accentuate the learning experience for students who learn best with social interactions [27, 28]. Overall, the design message to take away is that personalized AI learning does not mean a singular modality for each student; rather, it is a rich blended experience that accounts for all student learning modes. This balanced approach is echoed by e-learning experts, who recommend giving “balanced consideration to all learning styles while developing any e-learning course” [17]. By building flexible and multimodal platforms, we accommodate various learner preferences and create a more engaging learning environment for everyone.

Finally, these results imply that teachers and educators implementing AI tools should consider individual differences. Training and support should be provided so instructors can help students get the most out of AI-based learning [13]. For example, a teacher might encourage an auditory-oriented student to use text-to-speech features or supplement the AI lessons with verbal summaries. In contrast, a kinesthetic learner might be guided towards interactive modules. The goal should be to use AI to enhance universal learning design, not to replace one rigid method with another [9]. When AI complements traditional teaching, it can free teachers to provide more personalized human interaction (boosting relatedness) while the AI handles adaptive practice (boosting autonomy and competence). Such a synergy could leverage the strengths of both AI and human instructors to ensure all students “thrive” in terms of well-being and learning [27, 28].

VI. Limitations and Recommendations

There are some limitations to be aware of when considering the findings of this study. First, the results cannot be assumed to be generalizable, due in large part to sampling only high school students using a single AI-based instructional platform. Therefore, caution should be taken when making assumptions about alternative learning contexts, ages, or types of AI platforms. Second, learning styles were measured by self-report (the VARK inventory), which measures learner preferences and not fixed cognitive abilities, potentially oversimplifying complex learner profiles. Third, subjective well-being was self-reported, using questionnaires that allowed for possible biases due to participant mood, response tendencies, or a novelty effect associated with it being AI-based learning. Fourth, due to the short-term nature of the study, conclusions cannot be made regarding the sustainability of wellbeing benefits over time. Finally, the platform used in this study may have limited opportunities for the SDT-related dimension of relatedness. This could be further explored through qualitative measures.

Future research should address the limitations identified in this study by pursuing a variety of suggestions. First, AI systems should stimulate greater inclusion by using multimodal models of instructional delivery to include audio, to more effectively consider more learners who prefer audio, or auditory, information when learning. Second, further experimental work should study hybrid models that connect AI-generated personalized learning with the traditional instruction provided by a human teacher. This pedagogical approach may promote a sense of connectedness and relatedness. Third, longitudinal studies are warranted to understand the sustainability of wellbeing benefits and the longer-term impacts on most educational outcomes. Fourth, researchers should include a broader variety of outcome measures, including (a) performance about socially comparative performance, (b) attitude measures towards learning tasks, motivation, and engagement, and (c) in different schooling contexts and cultures. Our field will have a much better understanding of how AI may best support the well-being of all types of learners fairly and effectively.

VII. Conclusions

The present study indicates that, given adequate consideration, AI learning platforms can improve high school students' subjective well-being in learning experiences, especially where autonomy and competence needs are catered for through a rich, multimodal forum. AI significantly benefited visual, read/write, kinesthetic, and partially multimodal learners. However, auditory learners did not appear to gain value beyond traditional approaches or any advantage. In light of SDT, it is clear that learning technology needs to meet basic human needs better, whilst the outcomes also raise issues about educational AI being inclusive of differences in learning to ensure collective equity in value gained. If we can address the current limitations and pursue the future research agendas suggested, we should be able to develop understandings around learner–AI interactions and develop educational contexts that ultimately support high well-being and successful learning, regardless of learning style preference for all students. These understandings will be vital for educators and developers as they continue to incorporate AI systems into didactic practice, such that the potential exists for every student to realize value.

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