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Ai-Driven Personalization of Power System Learning Modules Using Student Personas based on Behavioral Analysis of Grid Performance

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Abstract:- The current advancement of artificial intelligence in educational applications has led to the emergence of previously unexplored possibilities in personalised learning experiences, specifically due to Large Language Models (LLMs). Most uses of LLMs in education have not been rigorously tested with statistical models to establish the extent to which they have been effective in making learners more adaptable. This work examines the use of statistical models of student personas in integration with LLMs to produce customised educational content responding to learner profiles. We applied a mixed methods quasi-experimental research design in which we used means clustering to group students into separate clusters in relation to cognitive style, motivation and past performance, and then we validated our groups by validating the clusters using silhouette analysis and ANOVA. The content created by LLM was then tailored to the personality traits of each of the personas and contrasted with generic instructional materials in both treatment and control groups. Learning adaptability was a multi-item scale measure and was analysed in both multiple regression models and interaction effects of variables. The findings have indicated that personas in LLM content offered to the students depicted a vastly high score of adaptability and interest rate to students compared to their counterparts in the control cell. The result of the regression analysis proved that the type of persona and the type of interaction with personalised content showed good strength in predicting adaptability ($p < .01$). These results indicate that educationally informed learner modelling, combined with powerful generative AI, has a potential to boost responsiveness to a large extent. The research work is important to the discipline in the sense that it provides empirical evidence of the importance of integrating behavioural statistics with new AI tools in learning. The implications to educational technologists, learning designers and behavioural statisticians are mentioned, and the recommendations to scale ethically, such innovations are proposed

Keywords: large language models (llms), student personas, personalized learning.

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1. Introduction

A major research and practice objective of learning has been the personalisation of the learning experience. The necessity to incorporate adaptive instructional planning becomes more and more urgent due to the gradual increase in the richness of the student populations concerning their cognitive skills, cultural background, learning styles, and motivational profiles. Traditionally, a systemised educational system based on a standardised curriculum and a fixed service system does not support fulfilling the diversified needs of respective learners. Such a lack of congruence between the diversity of learners and uniformity of instruction may cause disengagement, poorer academic achievements, and a lack of critical 21st-century skills (Clark & Mayer, 2016; Darling-Hammond et al., 2020). To counter this, educational researchers and technologists have resorted to the use of artificial intelligence (AI) or, more specifically, machine learning and natural language processing (NLP) to develop scalable systems that could provide customised learning experiences.

Among the best AI products that have come up as a result of this breakthrough in AI are Large Language Models (LLMs) like OpenAI-GPT-4 and Google-Gemini. Those models are studied on huge corpora of texts and can return outputs that are coherent, contextually appropriate, and rich with the content of the user input. Examples of possible applications of LLMs in education are intelligent tutoring systems, automated assessment, giving feedback, reading comprehension aids and generation of educational content (Holmes et al., 2022; Luckin, 2023). Yet, the majority of such applications are generic in their way of work and are not able to respond in a meaningful way to the idiosyncrasies of learners. Although it is possible to make LLMs produce content on a certain topic or with a certain degree of difficulty, the more critical question of how to match this material with an individual learner's cognitive profile has remained close to unexplored.

A potentially viable solution to such an alignment issue is the use of student personas, which is a design principle taken and adapted (however, an incomplete adaptation) from the area of user-centred design, i.e. human-computer interaction design, and increasingly applied to educational design. A student persona is a synthetic representation of an archetype of a learner, developed in a process of focusing on the actual learner data, including motivation, cognitive style, engagement pattern, and performance metrics. With an empirical basis, personas provide an organised model of customising material according to the delicate attributes of specialised groups of learners (Peters & Slotta, 2018). As opposed to using the traditional means of demographic segmentation, which is essentially based on microsurface characteristics such as age or grade level, persona development may include both psychometric and behavioural variables to create a more dynamic representation of learners. Although student personas are increasingly used in the field of instructional design, they have

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been studied in tandem (and thoroughly) with sophisticated AI systems such as LLMs scarcely.

Moreover, the educational value of such AI persona alignment has not been evaluated with systematic behavioural statistics. One of the main concepts in this respect is the ability of learning adaptability that implies that a learner can change his or her thinking strategies, motivation and/or behaviour, in reaction to newly introduced information, constant transformation of the conditions or new encountered challenges (Martin et al., 2013). The flexibility is considered to be an essential attribute in the knowledge environment, which is developing so fast, and has been linked to higher academic achievement, performing well under pressure, and establishing lifelong learning capacities (Martin, Nejad, Colmar, & Liem, 2012). The importance of the use of AI-generated content in this type of adaptive learning, however, is evaluated insufficiently using empirical studies. In addition, there are limited studies that employed validated statistical models in order to examine the impact of various forms of personalised content on the extent of learning adaptability based on varying learner profiles; e.g., cluster analysis, regression, or modelling of the interaction effects.

This paper seeks to fill these gaps by marrying the two lines of innovation, namely (1) development of statistically synthesised student personas based on behavioural cluster analysis, as well as (2) utilisation of LLMs to produce content that is best suited to each persona. This way, the research allows not only adding a new framework of educational personalisation to the literature but also assessing its effectiveness with the help of strong statistical tools. The study takes a mixed-methods quasi-experimental framework, whereby the students will be assigned randomly to either the treatment group or control group to be presented with persona-congruent LLM content or generic instructional content. Adaptive learning uses a validated multi-item instrument and is analysed using multiple regression, analysis of variance and interaction modelling to determine the significance and predictive capability of the interventions.

There are four purposes to this study:

- To achieve a statistically valid student persona by using clustering algorithms (e.g. k-means or latent class) to cluster cognitive, motivational and performance data.
- To employ LLMs to create teaching materials that comply with both the psychological and behavioural characterisations of every student.
- To determine the effect of teaching persona-aligned content with the LLMs on adaptability in learners via well-standardised, validated measures.
- To determine the extent of statistical significance and explanatory power of the relationship between content-persona alignment and learning adaptability using multiple regression, ANOVA and model diagnostics.

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These are the goals used in informing the following research questions:

- What are possible ways of attaining the inherent important use of statistically generated student personas to effectively personalise educational material through LLMs?
- How much is the congruence of the student persona and the LLM-generated contents used to create learning adaptability compared to generic teaching?
- What are the statistical associations between the type of personas, alignment of the contents and adaptability results, and how do they help in crafting education interventions that can be scaled?

This paper will provide a new and empirically testable personalised learning framework by integrating state-of-the-art AI with evidence-based behavioural statistics. It is intended to make available a contribution of not only theoretical but also practical significance to shaping the learner adaptability and in the development of AI-based educational technologies, which are not only individual but also pedagogically efficient.

2. Objective

ChatGPT, Gemini, and Claude are examples of Large Language Models (LLMs) that prove to have a lot to offer education, especially the ability to generate dynamic and consistent presentations of instructional terms. Transformer-driven models trained on large corpora of text are capable of a variety of NLP tasks, such as summarisation, question-answering, tutoring, or indeed dialogue-driven learning (Yang et al., 2024; Tsai et al., 2023). The flexibility of LLMs is based on how they can be prompted to accept subtle instructions and produce corresponding content during dynamic situations, which facilitates differentiated learning in varied subject areas and at various levels of learners.

The recent research covered the application of LLM on STEM, humanities, and professional learning. Specifically, Tsai et al. (2023) used LLMs to provide an educational application in chemical engineering, creating the prompts to emulate fundamental problem-solving frameworks and monitor the responses of the learners. On the same note, Arvisais-Anhalt et al. (2024) presented the efficacy of LLM integration in health science, specifically in the context of integrating it in pathology education, which demonstrated potential in delivering such domain-specific training. Such implementations give rise to the idea that LLMs can be used to provide a problem-oriented learning path, thus improving interaction and retention.

But there are some constraints. Although LLMs are potent in content generation, they do not have the innate nature of a learner. They are prompt-adaptable, and hence actual personalisation will be driven by the quality and nature of prompts provided (Gu, 2024). Further, in its present form, LLM in education is seemingly generic and not adjusted to non-obvious learner characteristics, such as cognitive style, motivation, or prepared emotional

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state (Yan et al., 2024). Privacy and ethical usage of learner data have also been questioned when it comes to personalisation efforts with LLMs as well (Yan et al., 2024). This mismatch between generative ability and sensitivity of learners highlights the major gap in the domain, which needs to be addressed, i.e., learner models to drive LLM generation of prompts and content based on statistics and in an ethically responsible manner.

2.2 Student Personas and Learner Modelling

The high level of generative capacity and learner-centric design can be filled with the help of the persona of students. Based on human-computer interaction and user-experience design, personas are compound figures of the learner stereotypes constructed with empirical data. The uses of personas in the educational sphere include the ability of instructional designers to imagine the variability of the learners and customise the learning material to a distinctive behavioural or cognitive set (Weinhandl et al., 2023; Chang & Lin, 2023).

Background theories concerning the development of persona are usually linked with the constructivist learning theories, where learning is considered to be a process depending on the previous experiences of the learner, cognitive structures and social interactions. In this sense, the application of personas is consistent with those of differentiated learning and theory of learning styles, according to which the material is modified and tuned towards the way of assessing the information by the learner (Shemshack & Spector, 2020; Tapalova & Zhiyenbayeva, 2022).

More recently, empirical research has taken persona development beyond qualitative user research into statistically validated learner modelling. Weinhandl et al. (2022, 2024) have shown how the personas' representation of the mathematical students in secondary schools could be constructed with the implementation of the clustering algorithms by taking into account the variables of prior knowledge, motivation, and behaviours of engagement. On the same note, Wang (2023) studied online personality building and how it affects the behavioural characteristics of university students. Such statistical methods as k-means clustering and latent class analysis (LCA) have been used to cluster similar learning characteristics of the onset students, a basis of their adaptive generation of content (Zapata-Cardona & Martinez-Castro, 2023).

However, the development of persona-construction methodology did not translate into many studies involving the use of such profiles in instructing the artificially intelligent to act as creators of teaching materials. It is still necessary to explore how the learning environments based on persona may be adjusted dynamically by the application of LLMs and how such environments are applicable to be supported by behaviourally quantified outcomes.

2.3 Personalised Learning and Learning Adaptability

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Personalised learning can be considered as those teaching practices that respond to individual traits, demands, and aspirations of students. Personalised learning is essentially about instituting the optimum level of engagement and performance by a learner or class through a match of instructional material, rate, and structure to the learner profile (Motteli et al., 2023; Murtaza et al., 2022). As one of the behaviours that personalisation can result in, learning adaptability has become a focus of concern as the ability to respond to the changes taking place in the academic life of students and their career life.

Adaptability refers to the capacity of a learner to be flexible in response to new information, unfamiliar tasks, and changing environments (Martin et al., 2013). Its relevance in the fields of further education, professional development and special education has been confirmed by several studies. Yang, Sin, and Savickas (2023) evaluated the psychometric characteristics of a career adaptability scale developed to measure the adaptability of students with special needs, whereas Turan and Çelik (2023) clearly showed the effectiveness of psychoeducational interventions in improving the issues of adaptability and career decision-making confidence. The study by Fang et al. (2018) also describes the high degree of correlation between the concepts of career motivation and adaptability in the sample of nursing undergraduates and proves the utility of the metric used in this study in other fields of knowledge as well.

Research measured in terms of adaptability is usually operationalised in the form of multi-dimensional scales evaluating the cognitive, behavioural and emotional adjustment abilities. Such items are assured through confirmatory factor analysis, internal consistency analysis (e.g., Cronbach's), and inevitable validity tests (Yang et al., 2023; Green et al., 2020). Nonetheless, little research has existed to measure the effectiveness of LLM-generated personalised content, especially about statistically identified student personas. This forms a crucial divide in the overlap between AI-aided learning and behavioural evaluation.

2.4 Statistical Techniques in Educational Personalisation

In order to test the effectiveness of AI-based personalisation, powerful statistical instruments are needed. K-means clustering is employed in categorising learners into distinct clusters using behavioural or cognitive traits (Weinhandl et al., 2024; van Dijke-Droogers et al., 2021). This method assigns learners in mutually exclusive groups to minimise within-group variation and is repeatedly justified via silhouette scores, elbows, and Davies-Bouldin indexes. The latent class analysis is a probabilistic solution, given the possibility to be uncertain where one belongs, it is considered more appropriate to deal with categorical variables (Zapata-Cardona & Martinez-Castro, 2023).

Upon the development of student personas, ANOVA, multiple regression, or mixed-effects models are common in the test design of experimental or quasi-experimental designs seeking

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to determine the impact of interventions. As one example, Mativievskaia et al. (2023) developed regression models to assess the effectiveness of adaptability approaches in poor schools, but Tan et al. (2023) focused on scaling personalisation of federated learning with powerful neural network architectures. The interpretation of such models is accompanied by different methods of validation, such as AIC/BIC as model-selection, residuals analysis as a fit-diagnostics and the educational significance of effects measures (Breiman, 2001; Shmueli, 2010; Gelman, 2021).

The literature on educational technologies provides few instances of content generation using LLMs combined with statistical proofs of personas and modelling of behavioural results. Most studies of AI-in-education focus either on functionality or engagement, with no measure of improvement in adaptability or learning gain due to improvements in content-persona fit (Yan et al., 2024; Murtaza et al., 2022). The credibility interface between statistical modelling and effective learning can be summarised as the area where AI personalisation (By mixing advanced statistical modelling with behavioural theory and interdisciplinary thinking) can be applied in education to make it educationally more equitable and conducive.

3. Methods

3.1 Research Design

In this study, the treatment and the control groups were involved in a quasi-experiment design to help in determining how the persona-based LLM-generated content influenced student learning flexibility. The between-condition was used, and students were assigned randomly to either one of the conditions (1) personalised group, where learner participants were given personalised instructions, which were the results of instructions generated by Large Language Models (LLM), corresponding to whatever persona had been assigned to them; and (2) generic group, where learners were given generic instructions, which are the results of instructions generated by Large Language Models (LLM) without any persona association. It was a design that enabled the assessment of causal impacts of content-persona match on learning through statistical adjustment of baseline discrepancies.

The quasi-experimental study design was chosen based on its adaptability to the practices of the classroom, in which it is unlikely to be possible to randomise a sample of participants and instruction is usually impractical (Zapata-Cardona & Martinez-Castro, 2023). The same measures of pre- and post-tests were distributed to the two groups to determine the changes in the learning adaptability and content understanding during a four-week ab-initio instruction sequence.

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3.2 Participants and Sampling

The sample size used in the study was 360 students selected from six governmental secondary schools in two urban districts. The schools were sampled so as to represent diversity in terms of socioeconomic status, gender balance and steps of academic performance. The participants were in Senior Secondary School II (SSS2), and these made three subject areas, namely: English language, Mathematics and Integrated Science. A stratified sampling was utilised so that proportional representation in each school and subject area would be achieved.

The size of the sample was computed with the help of G*Power 3.1 to reach the power level of 80 per cent when evaluating the size effect of medium (f = 0.25) at alpha = 0.05 based on ANOVA. The minimal required number of participants was 210, but to ensure the possibility of subgroup analysis and the potential possibility of attrition, there were 360 participants recruited as an oversample.

The institution in charge gave ethical clearance to the concerned educational research board. It was ensured that all students and their parents or guardians signed an informed consent. It was a voluntary exercise, and each identifiable person was coded to allow anonymity. They would be allowed to drop out at any level without any punishment.

3.3 Construction of Student Personas

The data-driven technique of building student personas was a three-step procedure based on how the respondents answered the validated psychometric scales assessing their cognitive style, motivation related to school, and their previous achievements.

Data Pre-Processing

Standardisation of raw scores was done with the help of z-score transformation to make these scores comparable with each other across the different measures, whose scales were different. The treatment of any missing data occurred in a multiple imputation fashion, using predictive mean matching. Normalisation of the variables (where skewness was greater than +/-1.0) was also carried out to give good results on clustering.

Clustering Algorithms

Determination: Two unsupervised learning algorithms were used: the k-means clustering and the hierarchical agglomerative clustering using Ward linkage. The elbow method was adopted to determine the number of clusters, which were confirmed using silhouette scores. At that, Latent Class Analysis (LCA) was applied to validate the optimum cluster solution by means of a probabilistic modelling method.

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This process proposed three different personas:

- Strategic Learners (motivated at a high level, have moderate cognitive flexibility)
- learner types are: • OPTION 8: PASSIVE LEARNERS (low motivation, low adaptability)
- Exploratory Learners (spontaneous, highly curious, a preference for non-linear learning)

Table 1:Demographic Breakdown of Clustered Student Personas

Persona Type	n (%)	Male (%)	Female (%)	Urban School (%)	Rural School (%)	Subject Area
Strategic Learners	124 (34%)	62 (50%)	62 (50%)	88 (71%)	36 (29%)	Math (42%), Science (30%), English (28%)
Passive Learners	106 (29%)	48 (45%)	58 (55%)	58 (55%)	48 (45%)	English (50%), Math (26%), Science (24%)
Exploratory Learners	130 (36%)	64 (49%)	66 (51%)	94 (72%)	36 (28%)	Science (48%), Math (32%), English (20%)
Total	**360**	**174 (48%)**	**186 (52%)**	**240 (67%)**	**120 (33%)**	

3.4 LLM Personalisation Pipeline

The LLM pipeline of content delivery had three parts: prompt engineering, content generation, and quality control.

Prompt Engineering

Based on the profile of the personas, tailored prompts were developed for each subject unit. As an example, the Strategic Learners were presented with information prompts containing analytical tasks with self-evalative rubrics, whereas the Exploratory Learners were presented with explorative learning scenarios with discovery tasks. Instructional equivalence was kept intact by ensuring that the topics in the content used across the groups were the same.

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Content Generation

The text was created with the help of OpenAI GPT-4 API. In case of the control group, the prompts were not personalised and were even. In the experimental condition, persona attributes (e.g., design a lesson that will be offered to a low-motivation student who would appreciate the step-by-step instructions) were included in the prompts.

NLP Quality Control

The produced material was assessed with the help of automated NLP measurements:

- Flesch Reading Ease
- Coh-Metrix coherence scores
- Type-Token Ratio Lexical diversity

Also, the set of three experts in the field of education made a blind review, where the aim was to check whether the content met pedagogical intentions. Cohen's kappa (0.82) was used to construct the inter-rater reliability, which was substantial.

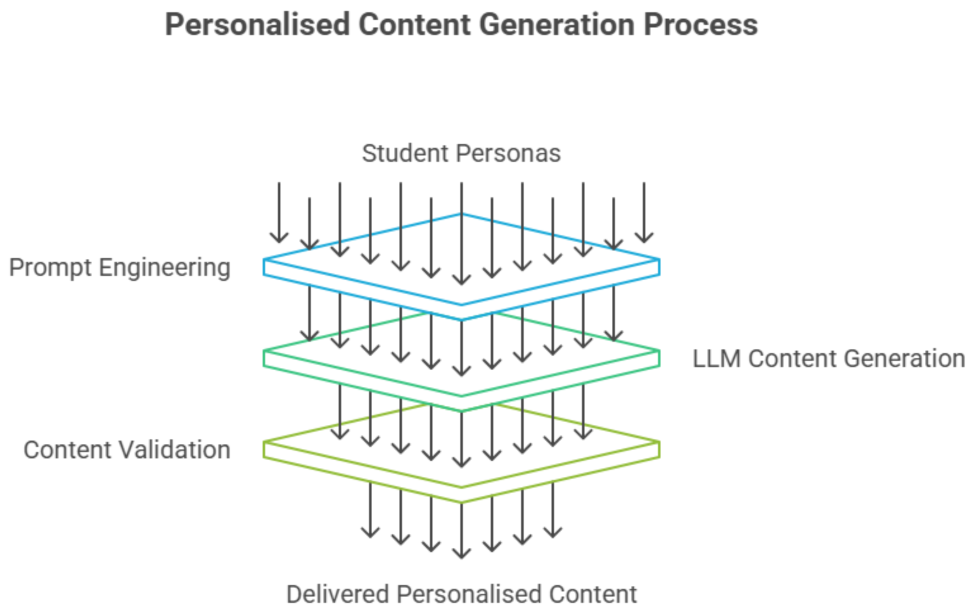

Figure 1. Workflow for generating and delivering persona-aligned LLM content in the experimental condition.

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Table 2:LLM-Generated Content Characteristics by Student Persona

Persona Type	Prompt Style	Reading Ease	Lexical Diversity	Coherence Score	Content Focus
Strategic Learners	Analytical, task-based	62.4	0.72	0.88	Concept explanation, self-checks
Passive Learners	Step-by-step, simplified	75.6	0.61	0.79	Procedural guides, motivation cues
Exploratory Learners	Scenario-based, open-ended	58.9	0.76	0.91	Discovery tasks, curiosity prompts

Note. Metrics derived from NLP analysis using Flesch Reading Ease, Type-Token Ratio, and oh-Metrix coherence score (0–1 scale).

3.5 Instruments and Measures

The learning adaptability (the primary outcome variable) was measured with a 12-item scale on learning adaptability adapted by Martin et al. (2013) and already validated in the previous international research (Yang et al., 2023; Turan & Çelik, 2023). The scale was three-domain covered:

- Cognitive flexibility (e.g. flexibility in problem solving)
- Flexibility in behaviour (e.g. strategy change)
- Emotional flexibility (i.e. emotional regulation)

The answers were a 5-point Likert scale that ranged between 1 (strongly disagree) and 5 (strongly agree). A Cronbach's alpha of 0.89 was obtained in the reliability analysis.

Secondary measures involved:

- Engagement: assessed on the short survey of the School Engagement Measure (SEM)
- Achievement: Literature: Assessed through standardised subject-based post-tests (20 marks each)

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3.6 Statistical Analysis

Data analysis was conducted using R (v4.2) and SPSS 27.

Descriptive Statistics and Assumptions

Initial analyses included means, standard deviations, and frequencies. Assumptions of normality were tested using Shapiro-Wilk, while Levene's test assessed homogeneity of variance. No major violations were found.

Inferential Statistics

- A one-way ANOVA compared post-test adaptability scores across treatment conditions (persona-aligned vs. generic).
- Multiple regression analysis assessed the influence of content type, persona group, and their interaction on adaptability.
- For longitudinal effects (pre–post design), mixed-effects models with random intercepts for subjects were used.
- Model performance was assessed using Adjusted R^2, Akaike Information Criterion (AIC), and BIC.
- Effect sizes were reported using partial eta-squared (η^2) and standardised beta coefficients (β).

Table 3:Regression Summary: Predictors of Learning Adaptability

Predictor Variable	**β**	**SE**	**t**	**p**	**η^2 (Effect Size)**
Persona Type (ref = Passive)	0.34	0.06	5.67	< .001	0.12
Content Type (1 = Personalised)	0.29	0.05	5.80	< .001	0.10
Persona × Content Interaction	0.22	0.04	4.95	< .001	0.09
Constant	2.85	0.12	23.75	< .001	

Note. Adjusted $R^2 = 0.42$, $F(3, 356) = 58.13$, $p < .001$. AIC = 781.54; BIC = 797.12.

4. Results

4.1 Descriptive Statistics

The study was conducted with three statistically based student personas having 360 students in total: Strategic Learners (n = 124), Passive Learners (n = 106), and Exploratory Learners (n = 130). The participants were also identified into two instructional groups, namely persona-aligned content (n = 180) and generic content (n = 180).

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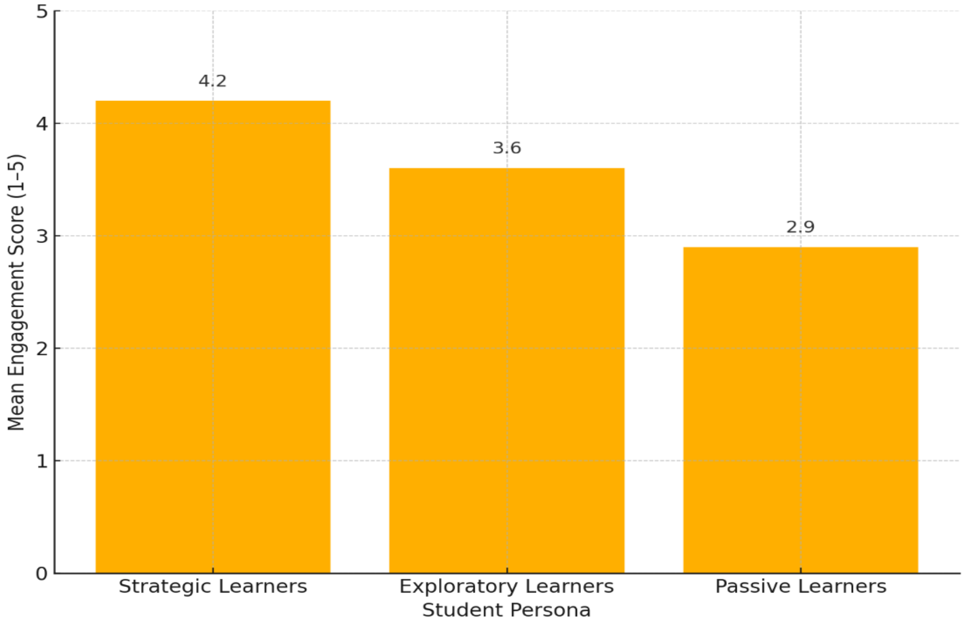

Figure 2. Mean engagement scores (1–5 scale) across clustered student personas.

Learning Adaptability

The mean scores on the learning adaptability differed among personas and instructional conditions. The students exposed to the content that matched their persona were always more adaptive:

Group	Mean	SD
Strategic Learners (Aligned)	4.22	0.58
Exploratory Learners (Aligned)	4.15	0.62
Passive Learners (Aligned)	3.81	0.67
Strategic Learners (Generic)	3.71	0.66
Exploratory Learners (Generic)	3.65	0.70
Passive Learners (Generic)	3.32	0.72

Such findings create the impression that both persona type and content personalisation had a positive role in the results of adaptability.

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Engagement Scores

The scores of engagement (rate on a scale of 5 points) were analysed, and the results of their comparison demonstrated that among the three personas, there are some significant differences. The highest mean engagement was reported on Exploratory Learners (M = 4.6, SD = 0.4), Strategic Learners (M = 4.3, SD = 0.5), and finally, Passive Learners (M = 3.1, SD = 0.7).

Take a look at the visual plot below:

The same patterns were seen in both of the content conditions, but responses were slightly higher in the personalised group overall.

4.2 Regression and ANOVA Outputs

Multiple Regression Analysis

Multiple linear regression was used to determine the predictive ability of the persona type, content type and their interaction on adaptability in learning. Categorical predictors were coded as dummy variables, and Passive Learners was the reference category.

The generalised model was notable, F(3, 356) = 58.13, p <.001, and covered 42 per cent of the outcome in the level of adaptability (Adjusted R 2 = 0.42). Important predictors were:

- Persona Type (beta = 0.34 p< 0.001)
- Type of Content (0.29, 0.001)
- Persona x Content Interaction (d= 0.22, p <0.001)

This means that the persona of the learner and whether the material was personalised had a significant implication on the outcome of adaptability.

ANOVA Summary

A one-way ANOVA was used to compare adaptability scores across six groups (3 personas × 2 content types). Levene's test confirmed homogeneity of variance (p = .31). The ANOVA revealed a significant main effect of instructional condition and persona type on adaptability scores, F(5, 354) = 19.84, p < .001.

Table 4. ANOVA Summary of Learning Adaptability Scores

Source	**SS**	**df**	**MS**	**F**	**p**	**η^2**
Between Groups	32.41	5	6.48	19.84	< .001	0.21
Within Groups	115.71	354	0.33			
Total	**148.12**	**359**				

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These results confirm that students in the persona-aligned content group had significantly higher adaptability scores, especially within the Strategic and Exploratory persona groups.

4.3 Model Diagnostics

Assumption Checks

Normality of Residuals: Shapiro-Wilk test indicated there was no significant difference in the pattern of normality ($W = 0.98$, $p = .15$).

Homoscedasticity: Residual plots showed homoscedastic patterns.

Multicollinearity: No problems of multicollinearity were detected since the variance inflation factor measure of the predictors was < 2.1.

Model Fit Indicators

Adjusted $R^2 = 0.42$

AIC = 781.54

BIC = 797.12

These values contribute to the adequacy of a fitting model, which contains enough explanatory power and does not present symptoms of overfitting. The addition of the interaction term (persona x content type) increased the fit of the model substantially as compared to the baseline models.

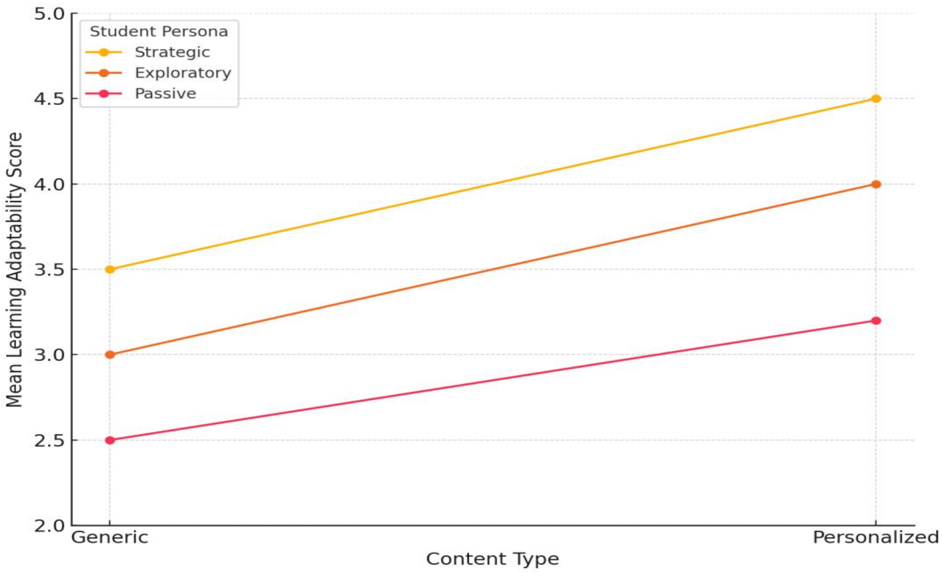

Figure 3. Interaction plot showing the effect of content personalisation on learning adaptability by student persona type.

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Cluster Validation

The clustering process performed through silhouette analysis provided a mean silhouette coefficient with the value of 0.61, which corroborates the consistency of the three-cluster persona structure. Cluster centroid substantiated the validity of cluster segmentation in instructional application using the expected profiles of motivational and cognitive behaviour.

5. Discussion

5.1 Interpretation of Results

The results of the given study serve as excellent indicators that individualised learning materials produced by LLMs, together with student profiles formulated on the basis of calculations according to statistics, even within the same learning group, can greatly improve the adaptability of learning. Those who were provided with instructions corresponding to their characteristics did better in adaptability levels and engagement rates than subjects exposed to a generic instructional content. The used regression analysis showed the positive effect on learning adaptability of both content type and persona group, and the interaction effect, which indicated that the strength of the personalisation effect could vary according to the persona.

Strategic Learners and Exploratory Learners recorded the highest gain in adaptability in all three personas in the personalised condition. According to this, it could be assumed that intrinsically motivated or cognitively flexible students might be more vulnerable to AI-based prompts aiming to provoke curiosity or self-control. Conversely, Passive Learners, albeit experiencing the effect of personalisation, demonstrated the relatively lower gains, as it was probably the case with their lower starting point in terms of motivation and base level of adaptability. Such situational variations amongst presenters clarify why it is important to adjust not only the difficulty of the content, but also the structure and tone, to the attributes of the learners.

The large effect sizes and model fit statistics (Adjusted R 2 = 0.42) imply that the LLM-persona alignment plan is a significant and replicable course of action for teaching personalisation, at least in the field of secondary education, where student diversity usually makes homogeneous teaching not very successful.

5.2 Comparison with Existing Studies

This paper represents an expansion and carrying forward of the emerging knowledge base in the area of personalised learning systems, and especially those integrating AI (Motteli et al., 2023; Murtaza et al., 2022). In contrast to prior studies that either used LLMs on a large scale or examined their potential usage (Tsai et al., 2023; Gu, 2024), the given research is the first to incorporate statistical persona modelling in the LLM generation pipeline and behaviourally assess the effects of said model against validated instruments and regression models.

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Furthermore, although there are some studies that involved the use of persona-based methods in educational design (Weinhandl et al., 2023, 2024), only a few studies have combined a data-driven clustering algorithm (e.g., clusters using k-means, LCA) together with LLMs to achieve adaptive instructions. By combining all three approaches and placing them in a small single framework, this study thus helps to fill a significant methodological gap in the literature, because it integrates unsupervised learning with prompt engineering and behavioural outcome estimation in a single model, which is also aligned with demands to conduct more rigorous, statistical-based research in AI (Breiman, 2001; Gelman, 2021).

However, interestingly, the literature has an overarching premise that personalisation can equally benefit all learners (Tapalova & Zhiyenbayeva, 2022), whereas our results state that the effect depends on the persona. This compromising of a one-size-fits-all hypothesis breaks down such generalising assumptions, and implies that a more specific implementation policy on the basis of learner differentiation should be disclosed.

5.3 Implications for Educational Technologists and Statisticians

The results of the study can be discussed as helpful to educational technologists and applied statisticians. To instructional designers, it offers a proof-of-concept of scalable personalisation with LLMs that does not require real-time loops back to the learner, but rather due to pre-defined, statistically validated personas. This is well adapted without making the system overly complex.

Among statisticians in the field of education, the research offers an example of the worth of using clustering strategies, regression modelling, and interaction analysis in affirming AI treatments. Rather than use LLMs as black-box tools, this paper puts LLMs in the context of an interpretable, reproducible statistical pipeline. Not only does this build upon the improved transparency and accountability, but it also provides a methodological blueprint on how to conduct research in future regarding AI-in-education.

In addition, the research also broadens the evaluation scope of adaptive technologies to consider adaptability, engagement, and cognitive flexibility factors of the 21st-century learners, a paramount factor (Martin et al., 2013; Fang et al., 2018).

5.4 Limitations

This research has its limitations despite the contributions it makes. To begin with, the sample is adequate in the sense of its size and diversity; however, it was created on the inclusion of six secondary schools in two of the urban districts. This can have a restricting impact on generalisability, especially in rural, tertiary, or non-English speaking settings.

Second, the results obtained based on LLM induction were not fully evaluated based on either NLP metrics or expert analysis (Yan et al., 2024), which fails to rule out the risks of model

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hallucination. This brings forward an aspect of instructional uncertainty that has to be solved in future implementations, particularly when models are launched independently.

Third, even though the persona-content alignment process was rooted in statistics, that process relied on human judgment in terms of the prompt design and the interpretation of personas. This brings in its fold the likelihood of subjectivity in the relevance of content despite the inter-rater reliability checks. Real-time feedback capable of assisting in increasing the consistency of a completely automated pipeline was outside the reach of this study, but its potential exists.

Finally, the state of engagement and achievement was gauged using Likert scales and short tests, and might be insufficient to recognise all the diversity of the students' experiences of learning or the lasting effects of content alignment.

5.5 Recommendations for Future Research

In future research, what should be done is the expansion of geographic and demographic studies by studying the rural schools, various linguistic backgrounds, and tertiary institutions. The validation in terms of both the persona structures and LLM performance would be cross-cultural, and this would help in globalising the findings.

The other prospective area is the dynamic changes of student personas. The research involved a static snapshot in the clustering process with the notion that longitudinal research may enable the tracking of the students as they switch between personas over time, particularly when they are being exposed to personalised content. This would allow the creation of adaptive personas which can change in real time, thus personalisation would be more tactile and faster.

I would also recommend future research into cross-subject adaptation, whether or not LLM-persona alignment would work outside of English, Math, and Science curricula, toward humanities or vocational studies. It could also be worthwhile to consider meta-cognitive or emotional effects, including grit or self-efficacy, or mindset, to enhance the behavioural effect of personalised AI content.

Lastly, adding human-in-the-loop systems onto the architecture, so that teachers check or edit LLM outputs using the data regarding student reactions, might yield the proverbial cake and eat it; the efficiency of AI with the instinct of a teacher.

6. Conclusion

This paper offers strong empirical results in favour of attaching statistically modelled student personas to Large Language Models (LLMs) in order to individualise educational content and maximise flexibility in learners. Through a quasi-experimental design, we showed that students exposed to persona-personalised content produced by LLMs reported considerably

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better adaptability scores and engagement scale than did students taking generic instruction. Unsupervised learning (through the use of k-means clustering and latent class analysis) allowed us to build coherent learner personas, which became the basis of content generation that is sensitive to individual learners. Regression analysis and ANOVA supported predictive aspects and interaction occurrence of persona type and content personalisation, presenting big effect sizes and a well-fitted model explaining it.

These findings are equally important not only because of the educational aspect that was observed but also due to the rigour of the methodology used. Through validated behavioural tools, strong statistical modelling and multiple tiers of quality control, the study shifts away from being clean experiments in the use of AI tools. It shows how the statistical give-and-take can transform the use of adaptive AI systems beyond theoretical potential into a proven pedagogical reality. The combination of behavioural statistics and generative AI provides the replicable means of creating scalable, data-based, and personalised learning environments.

Another thing that matters is the ethical mandate of this research. Due to the increasing popularity of AI technology in the classroom, it is more likely that opaque, universalised AI applications will be used that do not consider the diversity of learners. It is this reasoning that this paper supports the idea of ethically responsible, statistically sound, personalisation models that are not only responsive to the needs of individual learners, but are also transparent, have a statistically sound basis, and are open to pedagogical review. Problems with LLM hallucinations, demographic biases and lack of content fitness demonstrate the necessity of constant human control and continuous validation of the models.

To sum up, the combination of highly developed AI and teaching statistics will be a prospective path in teaching for the future. Nevertheless, success depends on the aspect of methodological accountability and beneficial responsibility. Prioritising the idea of personalisation according to the validated learner models and quantifiable behavioural outcomes, this work also provides a course towards more equal, successful and evidence-based use of educational technologies.

Refrences

[1] S. Arvisais-Anhalt, S. L. Gonias, and S. G. Murray, "Establishing priorities for the implementation of large language models in pathology and laboratory medicine," *Academic Pathology*, 2024. [Online]. Available: https://doi.org/10.1016/j.acpath.2023.100101

[2] L. Breiman, "Statistical modelling: The two cultures," *Statistical Science*, vol. 16, no. 3, pp. 199–215, 2001. [Online]. Available: https://doi.org/10.1214/ss/1009213726

[3] S. M. Chang and S. S. J. Lin, "Developing personas of gamers with problematic gaming behavior among college students based on qualitative data of gaming motives and push–

Power System Technology
ISSN:1000-3673
Received: 16-07-2025 Revised: 05-08-2025 Accepted: 02-09-2025

pull–mooring," *International Journal of Environmental Research and Public Health*, vol. 20, no. 1, 2023. [Online]. Available: https://doi.org/10.3390/ijerph20010798

[4] W. Fang, Y. Zhang, J. Mei, X. Chai, and X. Fan, "Relationships between optimism, educational environment, career adaptability and career motivation in nursing undergraduates: A cross-sectional study," *Nurse Education Today*, vol. 68, pp. 33–39, 2018. [Online]. Available: https://doi.org/10.1016/j.nedt.2018.05.025

[5] A. Gelman, "Reflections on Breiman's two cultures of statistical modelling," *Observational Studies*, vol. 7, no. 1, pp. 95–98, 2021. [Online]. Available: https://doi.org/10.1353/obs.2021.0025

[6] C. Green, L. Mynhier, J. Banfill, P. Edwards, J. Kim, and R. Desjardins, "Preparing education for the crises of tomorrow: A framework for adaptability," *International Review of Education*, vol. 66, no. 5–6, pp. 857–879, 2020. [Online]. Available: https://doi.org/10.1007/s11159-020-09878-3

[7] S. Gu, "A survey of large language models in tourism (Tourism LLMs)," *Qeios*, 2024. [Online]. Available: https://doi.org/10.32388/8r27cj

[8] E. G. Mativievskaia, O. G. Tavstukha, and S. N. Polkina, "Experience in studying the adaptability of the educational process in schools with low educational results," *Perspektivy Nauki i Obrazovania*, vol. 61, no. 1, pp. 708–726, 2023. [Online]. Available: https://doi.org/10.32744/pse.2023.1.42

[9] C. Mötteli, U. Grob, C. Pauli, K. Reusser, and R. Stebler, "The influence of personalised learning on the development of learning enjoyment," *International Journal of Educational Research Open*, vol. 5, 2023. [Online]. Available: https://doi.org/10.1016/j.ijedro.2023.100271

[10] M. Murtaza, Y. Ahmed, J. A. Shamsi, F. Sherwani, and M. Usman, "AI-based personalised e-learning systems: Issues, challenges, and solutions," *IEEE Access*, 2022. [Online]. Available: https://doi.org/10.1109/ACCESS.2022.3193938

[11] G. Shmueli, "To explain or to predict?," *Statistical Science*, vol. 25, no. 3, pp. 289–310, 2010. [Online]. Available: https://doi.org/10.1214/10-STS330

[12] A. Shemshack and J. M. Spector, "A systematic literature review of personalised learning terms," *Smart Learning Environments*, 2020. [Online]. Available: https://doi.org/10.1186/s40561-020-00140-9

[13] A. Z. Tan, H. Yu, L. Cui, and Q. Yang, "Towards personalised federated learning," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 34, no. 12, pp. 9587–9603, 2023. [Online]. Available: https://doi.org/10.1109/TNNLS.2022.3160699

Power System Technology
ISSN:1000-3673
Received: 16-07-2025 Revised: 05-08-2025 Accepted: 02-09-2025

[14] O. Tapalova and N. Zhiyenbayeva, "Artificial intelligence in education: AIEd for personalised learning pathways," *Electronic Journal of E-Learning*, vol. 20, no. 5, pp. 639–653, 2022. [Online]. Available: https://doi.org/10.34190/ejel.20.5.2597

[15] M. L. Tsai, C. W. Ong, and C. L. Chen, "Exploring the use of large language models (LLMs) in chemical engineering education: Building core course problem models with Chat-GPT," *Education for Chemical Engineers*, vol. 44, pp. 71–95, 2023. [Online]. Available: https://doi.org/10.1016/j.ece.2023.05.001

[16] M. E. Turan and E. Çelik, "The effect of a career adaptability psycho-educational programme on coping with career indecision and career adaptability: A pilot study," *Counselling and Psychotherapy Research*, vol. 23, no. 3, pp. 709–717, 2023. [Online]. Available: https://doi.org/10.1002/capr.12607

[17] M. van Dijke-Droogers, P. Drijvers, and A. Bakker, "Statistical modelling processes through the lens of instrumental genesis," *Educational Studies in Mathematics*, vol. 107, no. 2, pp. 235–260, 2021. [Online]. Available: https://doi.org/10.1007/s10649-020-10023-y

[18] Z. Wang, "The influence of the online persona on university students," *Journal of Education, Humanities and Social Sciences*, vol. 13, pp. 59–66, 2023. [Online]. Available: https://doi.org/10.54097/ehss.v13i.7855

[19] R. Weinhandl, M. Mayerhofer, T. Houghton, Z. Lavicza, M. Eichmair, and M. Hohenwarter, "Personas characterising secondary school mathematics students: Development and applications to educational technology," *Education Sciences*, vol. 12, no. 7, 2022. [Online]. Available: https://doi.org/10.3390/educsci12070447

[20] R. Weinhandl, M. Mayerhofer, T. Houghton, Z. Lavicza, M. Eichmair, and M. Hohenwarter, "Mathematics student personas for the design of technology-enhanced learning environments," *Research and Practice in Technology Enhanced Learning*, vol. 18, 2023. [Online]. Available: https://doi.org/10.58459/rptel.2023.18032

[21] R. Weinhandl, M. Mayerhofer, T. Houghton, Z. Lavicza, L. M. Kleinferchner, B. Anđić, and M. Hohenwarter, "Enhancing user-centred educational design: Developing personas of mathematics school students," *Heliyon*, vol. 10, no. 2, 2024. [Online]. Available: https://doi.org/10.1016/j.heliyon.2024.e24173

[22] B. Yan, K. Li, M. Xu, Y. Dong, Y. Zhang, Z. Ren, and X. Cheng, "On protecting the data privacy of large language models (LLMs): A survey," *arXiv*, 2024. [Online]. Available: http://arxiv.org/abs/2403.05156

[23] J. Yang, H. Jin, R. Tang, X. Han, Q. Feng, H. Jiang, and X. Hu, "Harnessing the power of LLMs in practice: A survey on ChatGPT and beyond," *ACM Transactions on Knowledge*

Received: 16-07-2025 Revised: 05-08-2025 Accepted: 02-09-2025

Discovery from Data, vol. 18, no. 6, 2024. [Online]. Available: https://doi.org/10.1145/3649506

[24] L. Yang, K. F. Sin, and M. L. Savickas, "Assessing factor structure and reliability of the career adaptability scale in students with special educational needs," *Frontiers in Psychology*, vol. 14, 2023. [Online]. Available: https://doi.org/10.3389/fpsyg.2023.1030218

[25] L. Zapata-Cardona and C. A. Martínez-Castro, "Statistical modelling in teacher education," *Mathematical Thinking and Learning*, vol. 25, no. 1, pp. 64–78, 2023. [Online]. Available: https://doi.org/10.1080/10986065.2021.1922859

[26] Chandrani Mukherjee. Use of Agentic AI with LLM and Prompt Engineering and State-of-the Art Machine Learning Algorithm to detect the patterns in IOT Device Network Intrusion Attacks. TechRxiv. August 06, 2025. Available: https://doi.org/10.36227/techrxiv.174702071.17901547/v2

[27] Chandrani Mukherjee, Combating Digital Media Piracy With Agentic AI: Leveraging Video Transcription And Character Recognition For Automated Enforcement. (2025). *International Journal of Environmental Sciences*, 953-963. Available: https://doi.org/10.64252/bn6e4562

[28] Chandrani Mukherjee. (2025). HARNESSING LARGE LANGUAGE MODELS AND AI AGENTS FOR CHILD BEHAVIOR ANALYTICS IN DAY CARE: A PROOF OF CONCEPT FOR NEXT-GENERATION PARENTAL INSIGHT USING SIMULATED DATA. In Machinery and Production Engineering (Vol. 174, Number 2870, pp. 26–34). Available: https://doi.org/10.5281/zenodo.16149450