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Beyond Behavioral Intention: A Context-Validated Framework for Meaningful Use of PictureThis AI in Ugandan Public Universities

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ABSTRACT

Purpose: This study validated and refined a context-specific framework explaining meaningful use behavior of PictureThis artificial intelligence (AI) for plant identification among undergraduate students in Ugandan public universities. Unlike an earlier analysis of predictors of behavioral intention from the same doctoral study, this article centres on the intention-to-use gap, actual academic engagement, mediation, moderation, and framework refinement.

Materials and Methods: A positivist, quantitative, cross-sectional correlational survey was conducted with 477 biological and agricultural science students from Makerere, Busitema, Gulu, and Kabale universities. After at least 30 days of guided PictureThis use, participants completed an adapted UTAUT2 questionnaire. Use behavior was operationalized as user cognitive absorption and deep-structure usage. Measurement and structural models, mediation, and moderation were evaluated with partial least squares structural equation modelling in SmartPLS 4.

Findings: The seven UTAUT2 predictors explained 62.7% of behavioral intention, but intention explained only 0.7% of meaningful use and did not significantly predict it ($\beta = .081$, $p = .252$). Hedonic motivation showed the clearest route to actual use, with a significant direct effect ($\beta = .143$, $p = .008$) and a significant indirect pathway through intention. Habit strongly predicted intention and retained an indirect pathway, whereas facilitating conditions were non-salient. Age moderated habit–intention and gender moderated price value–intention; most other demographic interactions were negligible.

Implications to Theory, Practice and Policy: The refined framework qualifies UTAUT2 by separating intention formation from meaningful academic use. Universities should move beyond awareness and stated willingness by embedding repeated, enjoyable, guided, and assessable AI-supported plant-identification tasks, while maintaining botanical verification, equitable access, privacy, and academic-integrity safeguards.

Keywords: *Picturethis AI; Use Behavior; UTAUT2; Plant Identification; Higher Education*

JEL Codes of Classification: *I21 (Analysis of Education); I23 (Higher Education and Research Institutions); O33 (Technological Change: Choices and Consequences)*

INTRODUCTION

Artificial intelligence applications increasingly mediate how students search, classify, interpret, and apply disciplinary knowledge. In biological and agricultural sciences, AI-enabled plant-identification applications can reduce the time and expertise required to generate a probable plant name from an image, while providing supplementary information about taxonomy, distribution, toxicity, and care. PictureThis is especially relevant because comparative evaluations have reported high identification performance among commonly available plant-identification applications (Hill, 2024; Schmidt et al., 2022). Such affordances may support fieldwork and practical learning where access to taxonomic experts, herbarium collections, field guides, and identification keys is limited.

Technology availability, however, does not ensure educationally meaningful use. Students may download an application, express willingness to continue using it, or open it occasionally without engaging deeply with its information. For plant-identification learning, meaningful use requires more than accepting the first AI-generated label. Students should inspect diagnostic features, compare candidate species, interpret taxonomic and ecological information, verify outputs against botanical evidence, and draw defensible conclusions. This study therefore conceptualized use behavior through user cognitive absorption and deep-structure usage rather than through access or frequency alone (Agarwal & Karahanna, 2000; Burton-Jones & Straub, 2006).

The extended Unified Theory of Acceptance and Use of Technology (UTAUT2) proposes that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and price value shape behavioral intention and use behavior, with selected relationships conditioned by age and gender (Venkatesh et al., 2012). Although UTAUT2 has been applied widely, much research privileges intention as the outcome or assumes that intention translates into use. That assumption deserves scrutiny in an academic context where deep use depends on instructional tasks, sustained practice, verification, and lecturer guidance.

A previous article from this doctoral project examined the salient predictors of behavioral intention to use PictureThis and showed that performance expectancy, effort expectancy, social influence, hedonic motivation, and habit significantly predicted intention (Bukenya et al., 2025). The present article does not repeat that contribution. It extends the analysis from willingness to meaningful behavior by testing the intention-use relationship, integrating mediation and moderation findings, and validating a parsimonious, context-specific framework for AI-supported plant-identification learning.

Problem Statement

A framework that retains empirically supported acceptance pathways for AI use in plant identification while identifying the pedagogical bridge between intention and actual, deep use in an academic context is not yet known. That bridge, in this study, refers to structured instructional guidance, cognitive absorption, and the use of PictureThis features for comparison, verification, and other higher-order plant-identification tasks. The study asked: Which UTAUT2 relationships remain salient when use behavior is defined as cognitive absorption and deep-structure usage, and how should the original framework be refined for Ugandan public universities?

The original framework was tested through the following directional hypotheses: H1, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and price value positively predict behavioral intention; H2, these seven UTAUT2 constructs positively predict meaningful use behavior; H3, behavioral intention positively predicts meaningful use behavior; H4, behavioral intention positively mediates the relationships between each UTAUT2 predictor and meaningful use behavior; and H5, age and gender significantly moderate the UTAUT2 relationships specified in the original model. Failure to support H3 would indicate an intention-use gap in this low-resource academic setting.

LITERATURE REVIEW

Theoretical Review

UTAUT integrated prominent technology-acceptance perspectives and proposed that performance expectancy, effort expectancy, social influence, and facilitating conditions explain behavioral intention and use, subject to demographic and experience-based contingencies (Venkatesh et al., 2003). UTAUT2 extended the theory to consumer contexts by adding hedonic motivation, price value, and habit and by specifying additional moderated paths (Venkatesh et al., 2012). Performance expectancy concerns expected task benefits; effort expectancy concerns ease of use; social influence captures important others' expectations; facilitating conditions represent resources and support; hedonic motivation concerns enjoyment; price value weighs benefits against monetary cost; and habit reflects automaticity arising from learning and repetition.

UTAUT2 is useful for AI-supported plant identification because it combines instrumental, social, affective, resource, economic, and routinization explanations. Yet its conventional use construct is often operationalized through self-reported frequency. The present study expands the educational meaning of use through cognitive absorption = the state of deep involvement with a technology, and deep-structure usage = the employment of system features to perform higher-order tasks (Agarwal & Karahanna, 2000; Burton-Jones & Straub, 2006). This operationalization makes a demanding test of the theory: a student can intend to use an app without becoming absorbed in it or using its features analytically.

Price value required particular attention because PictureThis operates on a freemium model. Students could access basic identification functions without a full subscription, but premium features, subscription charges, and mobile-data costs could affect the perceived balance between benefits and financial sacrifice. In a setting where disposable income and reliable connectivity are constrained, students may report favorable intentions while limiting exploration of advanced features. Price value was therefore interpreted as the perceived benefit of PictureThis relative to both direct subscription costs and the recurring cost of data access, with possible consequences for deep-structure usage.

Empirical UTAUT2 studies report heterogeneous pathways. Habit, performance expectancy, facilitating conditions, and hedonic motivation have been influential in mobile-application contexts, but effect sizes and significance vary with technology, task, and population (Gupta & Dogra, 2017; Palau-Saumell et al., 2019). Such variation supports contextual validation rather than wholesale transplantation of the original model. PLS-SEM is suited to this task because it accommodates complex predictive models with latent constructs, mediation, and moderation (Akter et al., 2017; Hair et al., 2021).

Conceptual Framework

The initial framework proposed direct paths from the seven UTAUT2 predictors to behavioral intention and use behavior; an intention-to-use path; mediation of each predictor-use relationship by behavioral intention; and selected age and gender interactions. Framework refinement followed a stated empirical retention rule. Paths with bootstrapped p-values below .05 were treated as statistically supported and considered for retention alongside theoretical relevance and effect-size interpretation. Paths with p-values of .05 or greater were removed from the predictive core or recast as implementation conditions when they remained educationally important. No separate minimum standardized path-coefficient threshold was imposed; this avoided discarding a statistically supported path solely because its coefficient was modest. The refined framework is shown in Fig. 1.

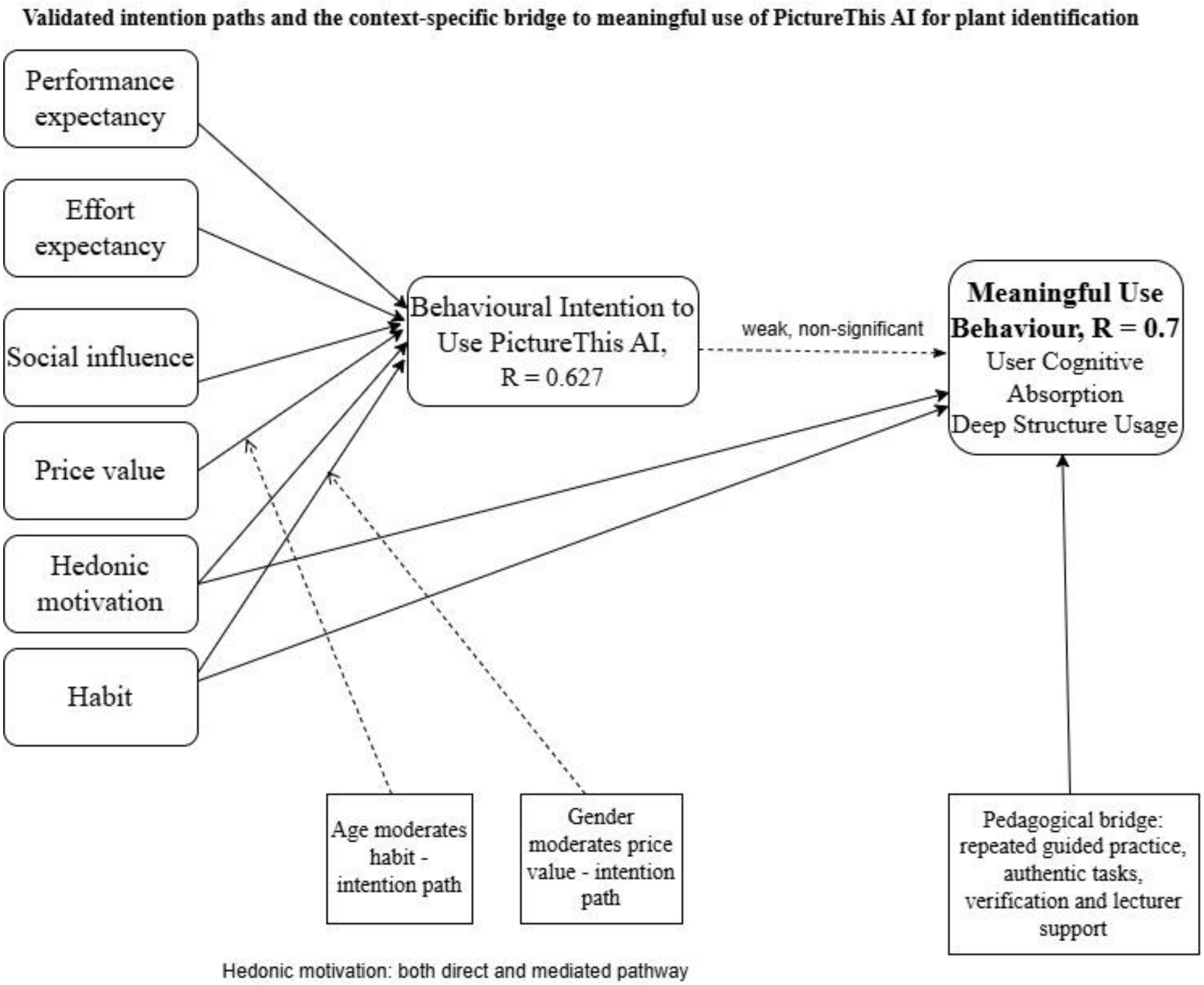

Figure 1: Validated and Refined Framework for Meaningful Use of PictureThis AI

Source: Author, based on the doctoral study (2026)

Research Gaps

Three gaps motivated the study. First, research on plant-identification applications has concentrated mainly on identification accuracy and user experience rather than the behavioral mechanisms of educational use. Second, much technology-acceptance research treats intention or simple usage frequency as the endpoint, leaving deep, disciplinary use insufficiently examined. Third, evidence from African public universities and low-resource science-learning contexts remains limited. The study addressed these gaps by testing UTAUT2 after authentic exposure to PictureThis, operationalizing use as cognitive absorption and deep-structure usage and refining the framework using evidence from four regionally distributed Ugandan public universities.

MATERIALS AND METHODS

Study Design: The study adopted a positivist, quantitative, cross-sectional correlational survey design. Study Location: Data were collected at Makerere University, Busitema University, Gulu University, and Kabale University, representing Uganda's central, eastern, northern, and western regions. Population and Sample: The target population comprised undergraduate students in biological and agricultural science programmes. A multistage strategy selected regionally distributed public universities, relevant programmes, and eligible students who owned a PictureThis-compatible smartphone. Although the minimum sample was 384 (Krejcie & Morgan (1970), 500 questionnaires were collected and 477 complete, eligible cases were analyzed.

Procedure and Data Collection: Research assistants guided participants to download and use PictureThis for at least 30 minutes per day over a minimum of 30 days in plant-identification activities. Compliance with the 30-day exposure requirement was established through participants' self-report at questionnaire administration; built-in screen-time trackers, application logs, and periodic researcher verification were not used. This reliance on self-report is acknowledged when interpreting actual-use findings. Participants then completed a self-administered questionnaire adapted from established UTAUT2 and system-use measures.

Measures: Standard items were reworded to refer specifically to PictureThis and to botanical and agricultural plant-identification tasks, including identification, comparison, verification, and interpretation of app outputs. Subject and research-method experts reviewed the contextualized items for relevance, clarity, and content coverage. The questionnaire was administered in English, the language of instruction at the participating universities, and no translated version was used. The instrument assessed performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, price value, behavioral intention, user cognitive absorption, and deep-structure usage on five-point response scales.

Quality Assurance: Content validity was supported through adaptation and expert review; convergent validity was assessed through factor loadings and average variance extracted; discriminant validity through HTMT ratios; and reliability through Cronbach's alpha and composite reliability.

Statistical Analysis: IBM SPSS Statistics 27 supported screening and descriptive analysis. SmartPLS 4 was used to assess measurement models and estimate direct, indirect, and moderated structural paths using bootstrapping. Significance was evaluated at $p < .05$.

Ethical Considerations: Participants received information about the study, anonymity and confidentiality were assured, findings were reported in aggregate, and institutional permission was sought for naming participating universities.

FINDINGS

Respondents and Measurement Quality

The final dataset comprised 477 complete responses. All 49 analyzed variables were complete, yielding 23,373 observed values without missing data. HTMT values were below .90, composite reliabilities exceeded 0.70, and retained indicators met the applicable loading and convergent-validity requirements after low-loading items were removed. These results supported interpretation of the structural paths. Respondents reported favorable overall behavioral intention ($M = 3.93$, $SD = 0.684$), while the use construct captured both immersion and meaningful application of app features rather than access alone.

Validation of the Intention Component

The combined non-moderated model explained 62.7% of the variance in behavioral intention (adjusted $R^2 = .624$). Performance expectancy, effort expectancy, social influence, hedonic motivation, and habit had positive, significant effects. Hedonic motivation was the strongest of these predictors ($\beta = .292$), followed closely by performance expectancy ($\beta = .278$). Facilitating conditions and price value were positive but non-significant in the combined model. Table 1 summarizes these paths; they establish that the intention-forming portion of UTAUT2 was largely valid in this context, while also reproducing the intention results reported previously (Bukenya et al., 2025) as the foundation for the present framework analysis.

Table 1: Combined Non-Moderated Predictors of Behavioral Intention

Path	B	T	P	Decision
Performance expectancy → intention	.278	6.011	< .001	Supported
Effort expectancy → intention	.118	2.541	.006	Supported
Social influence → intention	.104	2.358	.009	Supported
Facilitating conditions → intention	.058	1.341	.090	Not supported
Hedonic motivation → intention	.292	5.811	< .001	Supported
Habit → intention	.106	2.291	.011	Supported
Price value → intention	.044	1.159	.123	Not supported

The Intention-to-Use Gap

Behavioral intention had a small positive but statistically non-significant direct effect on meaningful use behavior ($\beta = .081$, $t = .668$, $p = .252$). Intention alone explained only 0.7% of the variance in use behavior (adjusted $R^2 = .007$). When all eight direct predictors were entered without mediation or moderation, the model explained only 3.4% of use behavior and none of the paths was significant. This sharp contrast between $R^2 = .627$ for intention and $R^2 = .007$ for use indicates that acceptance beliefs explain willingness substantially better than they explain cognitively absorbed, deep academic use.

Table 2: Direct Prediction of Meaningful Use Behavior

Model/Path	β or R²	t	P	Interpretation
Behavioral intention → use behavior	.081	.668	.252	Not significant
Intention-only model R²	.007	—	—	0.7% explained
Eight-predictor direct model R²	.034	—	—	3.4% explained
Moderated full model R²	.010	—	—	1.0% explained

4.4 Mediation and Salient Routes to Use

The construct-specific models clarified how students moved beyond intention. Hedonic motivation positively predicted intention ($\beta = .525$, $p < .001$) and use behavior directly ($\beta = .143$, $p = .008$); its indirect pathway through intention was also statistically significant ($\beta = -.071$, $p = .014$). Habit strongly predicted intention ($\beta = .510$, $p < .001$), while its direct use path was not significant ($\beta = .087$, $p = .082$); the reported indirect pathway through intention was significant ($\beta = -.064$, $p = .036$). The negative signs of the intention coefficients within these construct-specific mediation models should be interpreted cautiously considering the weak overall intention–use relationship and possible suppression. The robust substantive conclusion is that enjoyment showed the clearest direct connection with deep use, while repeated engagement strengthened intention and contributed indirectly.

Table 3: Hedonic Motivation and Habit Pathways to Use Behaviour

Path	B	T	p	Decision
Hedonic motivation → intention	.525	13.890	< .001	Supported
Hedonic motivation → use	.143	2.397	.008	Supported
Hedonic motivation → intention → use	−.071	2.209	.014	Supported
Habit → intention	.510	14.037	< .001	Supported
Habit → use	.087	1.394	.082	Not supported
Habit → intention → use	−.064	1.794	.036	Supported

Selective Moderation and Framework Refinement

Most hypothesized age and gender interactions were not statistically significant. Age did not moderate facilitating conditions-use ($\beta = .047$ for the direct path; interaction $p > .05$) or habit-use path (interaction $\beta = .002$, $p = .480$, $f^2 = .002$). The sampled students therefore translated support and habitual tendencies into use similarly across age groups. Two intention-related boundary conditions were retained: age moderated the habit–intention relationship, and gender moderated the price value- intention relationship. Price value became contextually relevant when gender was considered, suggesting that subscription and data costs may not operate uniformly across students.

The validated framework consequently has two layers. The first retains performance expectancy, effort expectancy, social influence, hedonic motivation, habit, and context-conditioned price value as antecedents of intention. The second recognizes that meaningful use is not produced by intention alone. Hedonic motivation repeated guided practice, authentic academic tasks, lecturer support, and verification activities form the practical bridge to cognitive absorption and deep-structure usage. Facilitating conditions remain an equity and implementation requirement but were not retained as a salient predictive path.

Discussion

The strong intention model is consistent with UTAUT2's central premise that usefulness, ease, social expectations, enjoyment, routine, resources, and price value shape acceptance (Venkatesh et al., 2012).

The prominence of hedonic motivation and performance expectancy indicates that students' willingness is simultaneously affective and instrumental: the application must be enjoyable, but it must also improve plant-identification work. Similar context dependence appears in research on mapping and restaurant applications, where habit, enjoyment, and usefulness have often been influential but demographic moderation has been inconsistent (Gupta & Dogra, 2017; Palau-Saumell et al., 2019).

The major theoretical result is the weak intention - use link. This divergence does not necessarily contradict students' favorable acceptance; it exposes the demanding operationalization of use. Cognitive absorption and deep-structure usage concern immersion, purposeful feature use, comparison, analysis, and conclusion-making (Agarwal & Karahanna, 2000; Burton-Jones & Straub, 2006). These behaviors require opportunities and tasks, not merely favorable beliefs. A student may intend to use PictureThis but still rely on its first suggestion superficially, use it only when prompted, or fail to verify the output botanically. Thus, intention should be understood as readiness, whereas meaningful educational use is an enacted learning practice.

Hedonic motivation's direct pathway suggests that immediate visual feedback and discovery can sustain attention long enough for meaningful interaction. Enjoyment is not a decorative feature in this setting; it can be an entry point into exploration. Nevertheless, enjoyment must be coupled with disciplinary structure. Without comparison against morphological features, keys, field guides, herbarium material, or expert judgement, an engaging identification result may foster uncritical acceptance. The refined framework therefore treats enjoyment and pedagogical verification as complementary.

Habit's role also requires a pedagogical interpretation. Routine is more likely to develop when lecturers embed the application across weekly practicals, field excursions, species inventories, and assignments. The non-significant direct habit - use path shows that repetition alone is insufficient; a learner can repeat a shallow action. Repeated tasks should progressively require deeper functions - examining diagnostic traits, comparing alternatives, checking scientific names, recording uncertainty, and defending a final identification.

The limited demographic moderation supports broadly inclusive implementation rather than extensive age- or gender-segmented instruction. Still, the significant age × habit and gender × price-value interactions identify targeted considerations. Students may differ in how routines shape their intention, while cost, data access, subscription affordability, and control over financial resources may carry gendered consequences. These findings justify monitoring equity without assuming universal demographic differences.

Finally, the low explained variance in actual use is analytically valuable rather than merely a weak result. It signals omitted, education-specific predictors. Lecturer integration, assessment design, digital competence, epistemic trust in AI, verification self-efficacy, task authenticity, feedback quality, data affordability, and sustained access may better explain deep academic use. The exposure period and use measures also relied on participant self-report rather than application logs or device-based screen-time records, which may have introduced recall or social-desirability bias. Future versions of the framework should test these factors longitudinally and combine self-report measures with app logs, submitted identification records, and performance assessments.

CONCLUSION AND RECOMMENDATIONS

Conclusion

The study validated UTAUT2 as a strong explanation of behavioral intention but a weak standalone explanation of meaningful PictureThis use among undergraduate biological and agricultural science students in Ugandan public universities. The seven predictors explained 62.7% of intention, whereas intention explained only 0.7% of use behavior and did not have a significant direct effect. The refined framework therefore separates acceptance from enactment. Usefulness, ease, social influence, enjoyment, habit, and context-sensitive price value build intention; meaningful use requires repeated, enjoyable, guided, and academically structured engagement. Age and gender are selective rather than universal boundary conditions. This framework extends the earlier intention-focused publication by explaining why willingness does not automatically become cognitive absorption and deep-structure usage.

Recommendations

Universities should integrate PictureThis into fieldwork, laboratory sessions, tutorials, assignments, and plant-identification projects rather than treating it as an optional download. Activities should require students to compare AI outputs with morphological evidence, taxonomic keys, field guides, herbarium specimens, and lecturer feedback. This positions AI as a complementary tool rather than a replacement for botanical reasoning.

Lecturers should design repeated and progressively demanding tasks that make use enjoyable while deepening disciplinary engagement. Guided field walks, species-discovery challenges, collaborative comparisons, uncertainty logs, and reflective verification reports can develop habit without normalizing superficial use. Assessment rubrics should reward justification, verification, and responsible interpretation, not merely production of a plant name.

University managers should sustain equitable access to compatible devices, internet connectivity, technical support, and affordable data or subscriptions even though facilitating conditions were not a significant predictor in the structural model. Predictive non-significance should not be interpreted as permission to neglect inclusion. Cost patterns should be monitored for gender-related inequities, while training should remain broadly accessible across age groups.

Higher education policy should establish guidance on accuracy verification, privacy, informed use of image and location data, academic integrity, accessibility, lecturer oversight, and the limits of automated identification. Further research should use longitudinal and mixed-method designs, objective usage traces, and learning performance measures to test additional predictors of deep use and to evaluate whether the refined framework generalizes to other AI applications, institutions, and disciplines.

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CONFLICTS OF INTEREST DECLARATION

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The dataset forms part of the corresponding author's doctoral research. Access may be considered by the author upon reasonable request and subject to the ethical and institutional conditions governing the study.