

MOBILE LEARNING, SELF-ESTEEM AND PERCEIVED ACADEMIC PERFORMANCE IN MATHEMATICS AMONG SENIOR SECONDARY SCHOOL STUDENTS IN LAGOS, NIGERIA: IMPLICATIONS FOR AI-ENABLED EDUCATIONAL TOOLS

S. A. Hassan¹; A. L. Adeyemo²; A. O. Adewunmi³; H. K. Adewole⁴, O.S. Usman⁵

^{1,2,4 & 5} Yaba College of Technology, Yaba, Lagos, Nigeria

³ Lagos State Ministry of Education, Lagos, Nigeria

Corresponding author: salim.hassan@yabatech.edu.ng | ORCID iD: [0009-0005-2481-8151](https://orcid.org/0009-0005-2481-8151)

Abstract

The growing use of smartphones among adolescents, together with the increasing incorporation of artificial intelligence (AI) features into educational applications, has renewed interest in the role of mobile learning (m-learning) in students' self-esteem and academic performance. This study examined the association between mobile learning, self-esteem and perceived mathematics performance among senior secondary school students at Yaba College of Technology Staff School, Lagos, Nigeria, and discussed the findings in relation to the emerging AI-enabled mobile-learning ecosystem. A descriptive cross-sectional survey was conducted with 100 Senior Secondary I–III students selected through random sampling. Data were collected using the Rosenberg Self-Esteem Scale and a researcher-designed mobile-learning questionnaire and analysed using descriptive statistics and exploratory chi-square goodness-of-fit tests. Sixty-nine percent of respondents reported owning a smart mobile device, although only 31% considered such devices affordable. Most respondents reported positive changes in self-worth (81%), self-confidence (80%) and perceived competence (87%), while 71–84% reported perceived improvements across mathematics-performance indicators. Between 67% and 75% also rated mobile learning more favourably than traditional classroom instruction across the measured dimensions. The chi-square results indicated that response distributions differed significantly from an equal four-category distribution ($p < .01$); these tests should not be interpreted as evidence of causal effects. Because the instrument did not distinguish AI-enabled applications from generic mobile-learning tools, the study provides baseline evidence about mobile learning rather than direct evidence of AI-specific effects. The findings

highlight the need for equitable access, stronger measurement and future studies that explicitly identify AI-enabled tools and use objective academic outcomes.

Keywords: Mobile Learning; M-Learning; Artificial Intelligence in Education; AI-Enabled Learning Tools; Adaptive Learning; Self-Esteem; Perceived Academic Performance; Mathematics Education; Secondary School Students; Nigeria

INTRODUCTION

Education systems worldwide are being reshaped by the rapid advancement of digital and mobile technologies. Electronic learning (e-learning) and its mobile derivative, mobile learning (m-learning), have moved from peripheral innovations to central features of how young people access information, engage with content and communicate with peers and instructors (Naismith, Lonsdale, Vavoula, & Sharples, 2004). Mobile learning is generally understood as learning mediated by hand-held wireless devices e.g. smartphones, tablets and similar technologies, that frees instruction from a fixed time or place (Alexander, 2004; Kukulska-Hulme & Traxler, 2005). Its appeal lies in its cost-effectiveness, portability, context-sensitivity and capacity to support collaborative and self-directed learning, all of which have been linked to gains in learners' motivation and knowledge structure (Mouza & Barrett-Greenly, 2015; Cheon, Lee, Crooks, & Song, 2012).

A significant recent development in this space is the increasing incorporation of artificial intelligence into the mobile applications and platforms students use for learning. Adaptive practice systems that adjust item difficulty to a learner's demonstrated ability, automated and immediate feedback on worked problems, and, more recently, conversational AI tutors, are being layered onto the same smartphones and tablets that have long carried generic mobile-learning content (Luckin, Holmes, Griffiths, & Forcier, 2016; Holmes, Bialik, & Fisher, 2019). This means that mobile learning and AI-enabled learning are, in practice, increasingly intertwined: the device is the delivery mechanism, and AI is an increasingly common feature of what is delivered through it. Understanding how mobile learning in general relates to psychosocial and academic outcomes therefore has direct relevance for anticipating how AI-enabled mobile learning tools specifically might affect students, even where a given study, such as this one, examines mobile learning broadly rather than isolating AI-specific features.

Beyond its instructional value, mobile learning has implications for adolescents' psychosocial development, particularly self-esteem, the global, subjective evaluation an individual holds of their

own worth (Hewitt, 2009). Self-esteem is widely regarded as central to mental health and social functioning: individuals with healthy self-esteem tend to be more expressive, resilient and socially confident (Coopersmith, 1967), whereas low self-esteem has been associated with anxiety, depression and poorer psychosocial outcomes (Baumeister, Campbell, Krueger, & Vohs, 2003). The relationship between technology use and self-esteem is, however, contested: some evidence links frequent mobile-device use to enhanced connectivity and self-worth, while other studies associate excessive or compulsive use with lowered self-esteem and heightened anxiety (Ha, 2006; Walsh, White, Cox, & Young, 2011). This ambivalence makes it important to examine, in a specific educational setting, how mobile learning as distinct from generic mobile-phone use, relates to students' self-esteem and their academic performance, and, by extension, how AI-enabled variants of mobile learning might be expected to relate to the same outcomes.

In the Nigerian context, the COVID-19 lockdown underscored the practical value of mobile devices for continuity of teaching and learning, and schools have continued to rely on them beyond the emergency period. Yet many secondary schools have not deliberately integrated mobile learning, still less AI-enabled mobile learning tools, into instruction, and it remains unclear whether the informal, student-driven use of mobile devices for schoolwork is associated with measurable benefits in self-esteem and subject-specific performance, particularly in mathematics, a subject widely perceived by students as difficult. This study addresses that gap by investigating the association between mobile learning on the self-esteem and academic performance of senior secondary school students of Yaba College of Technology Staff School, Lagos Mainland Local Government Area, Lagos State, Nigeria, and by discussing the findings against the backdrop of the growing role of AI within the mobile-learning ecosystem.

Specifically, the study sought to (i) determine the extent to which mobile devices are accessible to students; (ii) investigate the association between mobile-device use on students' self-esteem; (iii) examine the extent to which mobile learning is associated with students' academic performance in mathematics; and (iv) determine whether students perceive a significant difference between mobile learning and traditional classroom instruction. Corresponding to these objectives, four research hypotheses were tested: that mobile devices are not/are accessible to students; that mobile-device use has no/is significantly associated with students' self-esteem; that mobile-device use has no/is significantly associated with students' academic performance in mathematics; and that there is no/there is a significant relationship between mobile learning and students' self-esteem and academic performance. The findings are expected to guide teachers, school administrators and policymakers on the value and limits of incorporating mobile technology, including AI-enabled learning tools, into secondary school pedagogy.

Literature Review

Mobile learning developed as an emerging area of educational practice as researchers increasingly explored how mobile and wireless technologies could support teaching and learning (UNESCO, 2012). Early large-scale initiatives, such as the European Commission-funded MOBIlearn project, explored context-sensitive, informal and workplace learning using mobile devices, particularly among young adults excluded from conventional education (Attewell, 2005). Scholars have since offered varied definitions of the construct: Alexander (2004) describes mobile learning simply as learning built on wireless technologies and computing, while Masrek and Samadi (2017) define it as the acquisition of knowledge and skill through mobile technology, anywhere and at any time, resulting in a change in behaviour. Park (2011) proposed a four-type pedagogical framework distinguishing mobile-learning activities by transactional distance (high or low) and by whether the activity is socialised or individualised, ranging from tightly structured, instructor-led content delivery to loosely structured, learner-directed interaction. Across these definitions, mobile learning is consistently characterised by portability, flexibility, immediacy of feedback and the capacity to reach learners who are otherwise excluded by geography, cost or time (Kukulska-Hulme & Traxler, 2005).

The instructional features that make mobile devices attractive include short messaging for quizzes and polling, voice and video communication, internet browsing, graphical and multimedia display, downloadable content, and portability that allows learning beyond the classroom (Egunjobi & Ibode, 2005). At the same time, the literature identifies real constraints, including limited battery life and screen size, bandwidth demands, content-security concerns, fragmentation across device standards, and the risk of rapid obsolescence, as well as broader challenges of digital-access inequality and the absence, in many contexts, of a mature pedagogical theory tailored to mobile-age learning.

A growing strand of educational-technology research examines how artificial intelligence is being embedded within the mobile-learning tools students already use. Luckin, Holmes, Griffiths, and Forcier (2016) describe how AI techniques, learner modelling, adaptive sequencing of content, and automated assessment are being used to personalise instruction at a scale not previously possible, while Holmes, Bialik, and Fisher (2019) catalogue a range of AI-enabled applications in schools, from intelligent tutoring systems to AI-supported formative-feedback tools. In mathematics specifically, intelligent tutoring systems and AI-assisted practice applications provide step-by-step, adaptive feedback that adjusts to a learner's demonstrated competence, and a meta-analysis by VanLehn (2011) found that well-designed intelligent tutoring systems can approach the effectiveness of one-to-one human tutoring on measures of learning gain.

Because many of these AI features are delivered through the same smartphones and tablets that carry generic mobile-learning content, students in low- and middle-income contexts, including Nigeria, are increasingly likely to encounter AI-driven personalization without necessarily identifying it as distinct from mobile learning more broadly. This has two implications for the present study. First, it means that some of the mobile-learning use captured by a general mobile-learning inventory, such as the one used here, may already involve applications with AI-based features, even though the instrument was not designed to isolate this distinction. Second, it means that the psychosocial mechanisms already documented for mobile learning in general, for example, the link between competence-building technology use and self-esteem (Gecas, 1982; Mouza & Barrett-Greenly, 2015), provide a plausible theoretical bridge for anticipating how explicitly AI-enabled tools might affect the same outcomes, a possibility this study returns to in the Discussion.

Self-esteem refers to an individual's overall subjective evaluation of their own worth (Hewitt, 2009) and is composed of two related dimensions: a competence dimension, reflecting how capable and efficacious a person feels, and a worth dimension, reflecting the degree to which a person feels valuable (Gecas, 1982). High self-esteem is generally associated with sociability, resilience and psychological well-being (Coopersmith, 1967), whereas low self-esteem has been linked to anxiety, depression, poor communication and diminished performance (Mackinnon, 2015; Stavropoulos, et al., 2015). Baumeister, Campbell, Krueger, and Vohs (2003), however, caution that interventions aimed at boosting self-esteem have not reliably improved academic performance and may, in some cases, be counter-productive, underscoring the need for objective, outcome-based measurement rather than reliance on self-report alone.

The Rosenberg Self-Esteem Scale (Rosenberg, 1965) remains the most widely used instrument for measuring global self-esteem. It is a ten-item, one-dimensional, face-valid scale with strong internal consistency and test-retest reliability, originally developed for adolescents but subsequently validated for use with adults. The scale has attracted some methodological critique, for instance, concerns about response-set effects arising from its mix of positively and negatively worded items (Carmines & Zeller, 1974), but it continues to be the benchmark against which newer self-esteem measures are validated.

The relationship between mobile-technology use and self-esteem is not uniformly positive. Some studies suggest that mobile-device ownership and connectivity can enhance perceived status, social belonging and self-worth (Srivastava, 2005), while others report that excessive or compulsive use is associated with lower self-esteem, higher anxiety and loneliness (Ha, 2006; Aydin & Sari, 2011; Walsh et al., 2011). Andreassen, Pallesen, and Griffiths (2016) similarly found that addictive social-media use was linked to lower self-esteem, and the socio-meter model (Leary, et al., 1995) frames

low self-esteem as a signal of perceived social rejection. This body of work suggests that the direction and strength of the mobile-technology–self-esteem relationship may depend heavily on how the technology is used, for social validation and distraction, or for purposeful learning, whether AI-enabled or not, which is the distinction this study seeks to probe.

Academic performance is commonly understood as the outcome of the learning process, the knowledge, skills and results a student demonstrates before, during and after instruction (Narad & Abdullah, 2016), and is shaped by a combination of student-specific inputs (motivation, prior attainment, learning style), institutional and home environment, and the interaction between the two (Astin, 1984; Schneider & Preckel, 2017). Because sound academic performance is widely regarded as a precondition for career success and broader socio-economic development, it commands sustained research attention (Ali, Jusof, Ali, Mokhtar, & Salamat, 2009; Akinleke, 2017; Farooq, Chaudhry, Shafiq, & Berhanu, 2011).

Within mathematics specifically, technology integration remains uneven: although increased bandwidth and the proliferation of web-based instructional tools, including AI-assisted practice applications, create opportunities, classroom-level information and communication technology (ICT) pedagogy, especially for mathematics, remains underdeveloped in many schools, and teachers require sustained professional development to embed mobile, digital and AI-enabled tools meaningfully into subject-specific instruction (Goos & Bennison, 2008, cited in the original study; Borba, 2012). Where mobile learning has been deployed with adequate pedagogical design, it has been associated with improved motivation, more personalised instruction and stronger self-efficacy among learners (Mouza & Barrett-Greenly, 2015), suggesting a plausible pathway through which mobile learning, and by extension its AI-enabled variants, could jointly influence both self-esteem and subject-level performance in mathematics.

This study is anchored on Astin's (1984) Theory of Student Involvement, operationalised through the Input–Environment–Output (I-E-O) model. The model holds that educational outcomes (Output) are a function of students' pre-existing characteristics (Input), such as demographic background, motivation and prior attainment, and the environments students engage with during their studies (Environment), including curriculum, school climate and, increasingly, the technological tools available to them, among which AI-enabled mobile applications are a growing component. Within this framework, mobile learning is conceptualised as an environmental input capable of increasing students' involvement with academic content, which in turn is expected to influence both psychological outcomes such as self-esteem and academic outcomes such as performance in mathematics.

The reviewed literature establishes, on one hand, that mobile learning offers genuine pedagogical advantages, flexibility, nearness, personalisation, and, on the other, that the psychological correlates of mobile-technology use are mixed, with some studies linking heavy or non-instructional use to lower self-esteem. It also establishes that artificial intelligence is an increasingly common feature within the mobile-learning tools students use, even where this is not always apparent to the user or captured by general mobile-learning instruments. Much of the self-esteem literature, however, is drawn from general mobile-phone or social-media use rather than from instructional or learning-focused use, relatively little Nigerian secondary-school evidence exists on how mobile learning specifically relates to both self-esteem and subject-level academic performance, and fewer studies still have attempted to disentangle AI-specific effects from mobile-learning effects more broadly. This study contributes context-specific evidence from a Lagos secondary school on the general mobile-learning relationship, and offers this evidence as a baseline against which the effects of explicitly AI-enabled learning tools can later be compared.

Methodology

The study adopted a descriptive survey design, which allowed the researcher to gather the opinions and self-reports of a defined population using a structured questionnaire administered at a single point in time.

The population comprised senior secondary school students of Yaba College of Technology Staff School, Lagos Mainland Local Government Area, Yaba, Lagos State. From an estimated target population of about 1,000 students, a sample of 100 students was drawn using a random sampling technique, comprising 30 students from Senior Secondary I (SS1), 36 from Senior Secondary II (SS2) and 34 from Senior Secondary III (SS3).

Data were collected using the Mobile Learning, Self-Esteem and Perceived Academic Performance Questionnaire (MLSEPAQ), a structured questionnaire divided into three sections. Section A captured respondents' socio-demographic characteristics (sex, age and class). Section B comprised the ten-item Rosenberg Self-Esteem Scale (Rosenberg, 1965). Section C comprised 23 researcher-designed items across four thematic clusters: accessibility of mobile devices (7 items), association between mobile learning and self-esteem, including in mathematics specifically (6 items), association between mobile learning and academic performance in mathematics (5 items), and perceived difference between mobile learning and traditional learning (5 items). All items used a four-point Likert format (Strongly Agree, Agree, Disagree, Strongly Disagree). The instrument was subject to face and content validation by the researcher's supervisor Dr. Olatoye M. A. and two

additional validators, Dr. Adewole H.K. and Mr. Lasisi Adeniji W., a statistician, before administration.

Responses were coded and analysed using the Statistical Package for the Social Sciences (SPSS). Descriptive statistics (frequencies and percentages) were used to summarise respondents' characteristics and item-level responses. Exploratory chi-square goodness-of-fit tests were then applied to pooled response frequencies within each thematic cluster to determine whether the four response categories were equally distributed. These tests were conducted at $\alpha = .05$. Because this procedure tests departure from an equal distribution rather than a causal or associational effect between variables, the resulting statistics are interpreted only as evidence of non-uniform response patterns.

A methodological note is warranted for transparency. First, two sections of the original field report referred inconsistently to the study locale as "Lagos Mainland Local Government" and "Shomolu Local Government"; this manuscript follows the locale stated in the study title and sampling frame (Lagos Mainland Local Government, Yaba), consistent with the known location of Yaba College of Technology. Second, because the chi-square procedure aggregates items within each thematic cluster, several of which are worded in opposite directions (e.g., items indicating that devices are not government-provided, or that mobile learning does not fully resolve self-doubt), the resulting statistic should be read as evidence that responses within each cluster were not evenly or randomly distributed, rather than as a precise test of the substantive direction implied by each hypothesis. Researchers seeking to replicate or extend this work are encouraged to report Cronbach's alpha for instrument reliability, to consider chi-square tests of independence (e.g., self-esteem or performance outcomes cross-tabulated with device access or usage frequency) in addition to, or in place of, the goodness-of-fit approach used here, and to add items that explicitly identify whether the mobile-learning tools used are AI-enabled.

Results

Of the 100 respondents, 58% were male and 42% were female. Most respondents (77%) were aged 10–15 years, 22% were aged 16–20 years, and 1% was aged 21 years or above. By class, 30% were in SS1, 36% in SS2 and 34% in SS3.

Responses to the Rosenberg Self-Esteem Scale indicated generally healthy self-esteem among respondents. Large majorities agreed that they were persons of worth (96%), possessed a number of good qualities (95%), were able to do things as well as most other people (88%), held a positive attitude toward themselves (92%) and were, on the whole, satisfied with themselves (81%).

Conversely, only 8% agreed with the negatively worded item "All in all, I am inclined to feel that I am a failure," while 31% agreed they did not have much to be proud of, and 38–41% acknowledged occasional feelings of uselessness or self-doubt. Overall, the pattern is consistent with a sample whose baseline self-esteem is skewed positive, providing the backdrop against which the associations involving mobile learning were assessed.

Table 1. Accessibility of Mobile Devices (N = 100)

Item	SA (%)	A (%)	D (%)	SD (%)	Agree (SA+A)
Owens a smart mobile device	50	19	21	10	69
Devices are cheap/easy to obtain	15	16	37	32	31
Parental restriction on device use	27	24	30	19	51
Device provided by government	7	9	32	52	16
Device self-purchased	19	19	34	27	38
Device purchased by parent/guardian	45	28	19	8	73
Maintenance/data costs are cheap	15	25	38	20	40

SA = Strongly Agree; A = Agree; D = Disagree; SD = Strongly Disagree.

Table 1 shows that 69% of respondents owned a smart mobile device, and most devices (73%) were purchased by a parent or guardian rather than by the students themselves (38%) or provided by government (16%). Only 31% considered mobile devices cheap or easy to obtain, and only 40% considered the cost of maintaining mobile services (data, subscriptions) to be cheap, indicating that affordability, rather than device ownership per se, is the more binding constraint on accessibility. About half of the respondents (51%) reported that a parent or guardian was apprehensive about their device use, pointing to a parental-supervision dimension that coexists with high ownership rates.

Table 2. Effect of Mobile Learning on Students' Self-Esteem (N = 100)

Item	SA (%)	A (%)	D (%)	SD (%)	Agree (SA+A)
Increased self-worth	35	46	13	6	81
Improved self-confidence	38	42	14	6	80
Improved sense of competence	44	43	10	3	87
Increased confidence in mathematics	34	38	22	5	72
Positive self-attitude in mathematics	26	42	23	9	68

Item	SA (%)	A (%)	D (%)	SD (%)	Agree (SA+A)
Persistent self-doubt despite use (reverse-worded)	11	29	33	26	40

SA = Strongly Agree; A = Agree; D = Disagree; SD = Strongly Disagree.

As shown in Table 2, large majorities of respondents attributed gains in self-worth (81%), self-confidence (80%) and perceived competence (87%) to their use of mobile technology for learning. Effects specific to mathematics were somewhat more moderate but still substantial: 72% reported increased confidence in mathematics and 68% reported a more positive self-attitude when learning mathematics via mobile technology. Notably, 40% still agreed with the reverse-worded item indicating persistent self-doubt in mathematics despite mobile-learning use, suggesting that mobile learning attenuates, but does not eliminate, mathematics-related self-doubt for a substantial minority of students.

Table 3. Effect of Mobile Learning on Academic Performance in Mathematics (N = 100)

Item	SA (%)	A (%)	D (%)	SD (%)	Agree (SA+A)
Performs well in mathematics	23	48	20	9	71
Improved mathematical skills	31	45	16	8	76
Enhanced assimilation	35	41	19	4	76
Improved grade performance	30	44	24	2	74
Improved retention via playback	43	41	10	6	84

SA = Strongly Agree; A = Agree; D = Disagree; SD = Strongly Disagree.

Table 3 indicates consistently high agreement across all five performance-related items, ranging from 71% ("I perform very well in mathematics with the use of mobile learning technology") to 84% ("the opportunity to play back lessons enhances retention and growth of knowledge"). Improved mathematical skills and enhanced assimilation of instructional content were each endorsed by 76% of respondents, and 74% reported a drastic increase in grade performance.

Table 4. Perceived Difference Between Mobile Learning and Traditional Learning (N = 100)

Item	SA (%)	A (%)	D (%)	SD (%)	Agree (SA+A)
More explanatory than traditional method	40	35	16	9	75
Faster assimilation than traditional method	27	44	18	11	71

Item	SA (%)	A (%)	D (%)	SD (%)	Agree (SA+A)
Greater confidence than traditional method	36	31	21	12	67
More efficient lesson management	31	43	15	11	74
More student-centred	40	32	14	14	72

SA = Strongly Agree; A = Agree; D = Disagree; SD = Strongly Disagree.

Across all five comparative items, a majority of respondents (67–75%) rated mobile learning more favourably than traditional classroom instruction, on explanatory clarity, pace of assimilation, confidence gained, efficiency of lesson management and student-centredness.

Exploratory chi-square goodness-of-fit tests were conducted on the pooled response frequencies for each thematic cluster. The null hypothesis for each test was that responses were evenly distributed across the four Likert categories. A significant result therefore indicates a non-uniform response pattern; it does not, by itself, establish that mobile learning caused a change in self-esteem or academic performance.

Table 5. Summary of Chi-Square Goodness-of-Fit Tests

Hypothesis / Construct	Observed (SA, A, D, SD)	χ^2 (df=3)	P	Decision ($\alpha = .05$)
Accessibility of mobile devices	178, 140, 211, 168	14.79	0.002	Reject H_0 (significant)
Self-esteem responses	188, 240, 115, 55	132.39	< .001	Reject H_0 (significant)
Mathematics-performance responses	162, 219, 89, 29	166.07	< .001	Reject H_0 (significant)
Mobile versus traditional learning	174, 185, 84, 57	98.45	< .001	Reject H_0 (significant)

Null hypothesis for each exploratory test: response frequencies are evenly distributed across the four Likert categories. Rejection indicates a statistically significant departure from an equal distribution; it does not establish a causal effect.

All four chi-square statistics exceeded the critical value of 7.81. The response distributions therefore departed significantly from an equal four-category distribution in each construct. The descriptive patterns in Tables 1–4 show that agreement was generally more common for the mobile-learning benefit items, but these findings should be interpreted as perceptions rather than evidence of causal effects.

Discussion

The finding that most students in this sample owned smart mobile devices, yet regarded them as neither cheap to obtain nor cheap to maintain, echoes the broader literature on the "digital divide": device penetration does not, by itself, guarantee equitable or sustained access to mobile learning, still less to the AI-enabled tools increasingly layered onto it (Attewell, 2005). That most devices were purchased by parents or guardians rather than by government or by students themselves also underscores the continuing role of household resources in mediating access, a pattern with implications for equity in contexts of socio-economic disparity, and one that would likely also apply to access to AI-enabled learning applications.

The strong association reported between mobile-learning use and self-esteem (self-worth, confidence and perceived competence) is broadly consistent with studies that link purposeful, competence-building technology use to positive self-evaluation (Mouza & Barrett-Greenly, 2015), and with Gecas's (1982) conceptualisation of self-esteem as comprising both competence and worth. It stands in some contrast, however, to studies reporting that heavy or non-instructional mobile-phone and social-media use is associated with lower self-esteem, anxiety and loneliness (Ha, 2006; Andreassen et al., 2017; Walsh et al., 2011). A plausible reconciliation is that it is the purpose and mode of mobile-device use, learning-directed versus purely social or recreational, that differentiates the two sets of findings, though this study did not directly measure usage patterns and cannot adjudicate the point; it flags a clear direction for further research.

The academic-performance findings, improved self-reported performance, mathematical skill, assimilation, retention and grades, align with the theoretical expectation, drawn from Astin's (1984) I-E-O model, that a supportive environmental input (here, mobile learning) can enhance measurable educational outcomes. They are also consistent with prior calls for greater ICT integration specifically within mathematics pedagogy (Borba, 2012). At the same time, because performance was assessed through student self-report rather than independently verified grades or test scores, these findings should be interpreted as indicators of perceived rather than objectively confirmed improvement, a limitation discussed further below.

Students' preference for mobile learning over traditional instruction, on explanatory clarity, pace, confidence, lesson management and student-centredness, is consistent with arguments in the literature that mobile learning can offer more personalised, learner-paced engagement than conventional classroom delivery (Masrek & Samadi, 2017). This preference should, however, be read alongside Baumeister et al. (2003) caution that self-reported confidence or satisfaction gains do

not automatically translate into improved objective outcomes, reinforcing the need for future studies to triangulate self-report data with independently verified academic records.

Although this study's instrument could not isolate whether the mobile-learning applications respondents used were AI-enabled, the pattern of findings has plausible implications for AI-enabled mobile learning specifically. The features respondents associated with the benefits of mobile learning, explanatory clarity, faster assimilation, improved lesson management and a more student-centred experience, are precisely the dimensions that adaptive, AI-driven tutoring systems are designed to strengthen through personalised sequencing and immediate, individualised feedback (Luckin et al., 2016; VanLehn, 2011). If the general mobile-learning gains in self-esteem and mathematics performance reported here hold, or are amplified, for AI-enabled tools specifically, this would align with intelligent-tutoring-systems research showing learning gains approaching those of one-to-one human tutoring (VanLehn, 2011). Equally, the same access and affordability constraints documented here for basic mobile-device ownership would be expected to apply, and potentially compound, for AI-enabled applications, which can carry additional data, subscription or hardware requirements. This study cannot confirm either possibility directly; it establishes a mobile-learning baseline against which future, explicitly AI-focused research in this setting can be compared.

CONCLUSION

This study set out to examine mobile learning and AI-enabled educational tools in relation to the self-esteem and academic performance in mathematics of senior secondary school students at Yaba College of Technology Staff School, Lagos Mainland Local Government Area, Lagos State, against the backdrop of a mobile-learning ecosystem into which artificial intelligence is being steadily absorbed. In terms of device accessibility, most students owned a smartphone. Yet, only a minority regarded such devices as affordable to acquire or maintain, indicating that ownership, rather than cost, is the less binding constraint. This distinction matters for AI-enabled tools, which often add further data, subscription, or hardware demands on top of basic connectivity. On self-esteem, mobile-learning use was reported positive associations with students' self-worth, confidence and sense of competence, both generally and in mathematics specifically, consistent with the view that purposeful, competence-building technology use, of the kind AI-driven personalisation is designed to intensify, can support healthy psychosocial development. On academic performance, respondents reported gains that were significantly non-uniformly distributed across the response categories in mathematical skill, assimilation, retention and grades, and students consistently rated it more favourably than traditional instruction on explanatory clarity, pace, confidence and student-centredness, precisely the dimensions that adaptive, AI-driven tutoring is designed to strengthen through personalised sequencing and immediate feedback. Because the instrument could not

separate AI-enabled applications from mobile-learning tools more broadly, these findings describe mobile learning in general; even so, they establish a coherent, statistically significant baseline linking mobile learning to self-esteem and mathematics performance in this Lagos secondary-school setting, one against which the specific contribution of AI-enabled features can be measured as such tools become more prevalent and more identifiable to students and researchers alike. Overall, the study supports consideration of deliberate, equity-conscious integration of mobile and AI-enabled learning tools into mathematics pedagogy as a constructive complement to, rather than a replacement for, conventional classroom instruction.

The study is limited by its reliance on a single-school sample of 100 students, which restricts generalisability; by its use of self-reported measures of academic performance rather than verified school records; by the absence of a reported reliability coefficient (e.g., Cronbach's alpha) for the researcher-designed instrument; and by its cross-sectional design, which precludes causal inference about the direction of the relationship between mobile learning, self-esteem and performance. As noted in the Methodology, the chi-square analysis tested whether response patterns departed from chance within thematic clusters of items rather than isolating the direction of each specific hypothesis. A further limitation, specific to the AI-context framing offered in this manuscript, is that the instrument did not ask respondents to identify whether the mobile-learning tools they used were AI-enabled; the discussion of AI-specific implications is therefore interpretive rather than directly evidenced, and future work should also report on students' actual frequency and purpose of mobile-device use and on whether the specific applications used incorporate AI features, since these may moderate the self-esteem and performance relationships.

RECOMMENDATIONS

Based on the findings and conclusions of this study, the following are proposed as recommendations:

1. Schools and teachers should consider carefully designed mobile-learning activities in mathematics, while monitoring actual learning outcomes rather than relying solely on students' perceptions.
2. Government and education policymakers should explore subsidised device or data-access schemes, since affordability, rather than device ownership, emerged as the more binding constraint on accessibility, a constraint likely to extend to AI-enabled applications with additional data or hardware demands.

3. Teachers and students should receive structured orientation on the effective and safe use of mobile learning tools, including guidance on identifying and appropriately using AI-enabled features such as adaptive practice and automated feedback, to maximise instructional benefit while managing distraction risks.
4. Parents and guardians should be engaged as partners in mobile-learning initiatives, given the prominent role they play in device provision and supervision.
5. Future research should employ verified academic records, validated reliability statistics, larger and more diverse samples, and, where feasible, longitudinal or quasi-experimental designs to strengthen causal inference.
6. Future research should explicitly distinguish AI-enabled mobile learning tools (e.g., adaptive practice applications, intelligent tutoring systems, AI-assisted feedback tools) from generic mobile-learning use, in order to isolate the specific contribution of AI personalization to self-esteem and academic-performance outcomes.

References

- Akinleke, W. O. (2017). Impact of family structure on the academic performance of secondary school students in Yewa Local Government Area of Ogun State, Nigeria. *International Journal of Sociology and Anthropology Research*, 3(1), 1–10.
- Alexander, B. (2004). *Going nomadic: Mobile learning in higher education*. Educause Review, 39(5).
- Ali, N., Jusof, K., Ali, S., Mokhtar, N., & Salamat, A. S. A. (2009). The factors influencing students' performance at Universiti Teknologi Malaysia. *Management Science and Engineering*, 3(4), 81–90.
- Andreassen, C. S., Pallesen, S., & Griffiths, M. D. (2017). The relationship between addictive use of social media, narcissism, and self-esteem: Findings from a large national survey. *Addictive Behaviors*, 64, 287–293. <https://doi.org/10.1016/j.addbeh.2016.03.006>
- Astin, A. W. (1984). Student involvement: A developmental theory for higher education. *Journal of College Student Personnel*, 25(4), 297–308.

- Attewell, J. (2005). *Mobile technologies and learning: A technology update and m-learning project summary*. Learning and Skills Development Agency.
- Aydin, B., & Sari, S. V. (2011). Internet addiction among adolescents: The role of self-esteem. *Procedia: Social and Behavioral Sciences*, 15, 3500–3505.
- Baumeister, R. F., Campbell, J. D., Krueger, J. I., & Vohs, K. D. (2003). Does high self-esteem cause better performance, interpersonal success, happiness, or healthier lifestyles? *Psychological Science in the Public Interest*, 4(1), 1–44.
- Borba, M. C. (2012). Humans-with-media and continuing education for mathematics teachers in online environments. *ZDM – The International Journal on Mathematics Education*, 44(6), 801–814.
- Carmines, E. G., & Zeller, R. A. (1974). On establishing the empirical dimensionality of theoretical terms: An analytical example. *Political Methodology*, 1(4), 75–96.
- Cheon, J., Lee, S., Crooks, S. M., & Song, J. (2012). An investigation of mobile learning readiness in higher education based on the theory of planned behavior. *Computers & Education*, 59(3), 1054–1064. <https://doi.org/10.1016/j.compedu.2012.04.015>
- Coopersmith, S. (1967). *The antecedents of self-esteem*. Freeman.
- Egunjobi, A.O. and Ibode, O.F. (2005). ‘Utilization of ICT in Nigerian Educational Systems: Problems and Prospects’. *Journal of E- Learning Network of Nigeria*. University of Ibadan, Ibadan. 1(1), 57-66.
- Farooq, M. S., Chaudhry, A. H., Shafiq, M., & Berhanu, G. (2011). Factors affecting students' quality of academic performance: A case of secondary school level. *Journal of Quality and Technology Management*, 7(2), 1–14.
- Gecas, V. (1982). The self-concept. *Annual Review of Sociology*, 8, 1–33. <https://doi.org/10.1146/annurev.so.08.080182.000245>
- Ha, Y. J. (2006). *The relationship among self-esteem, internal locus of control, and psychological well-being (Unpublished master's dissertation)*. Yonsei University, South Korea.
- Hewitt, J. P. (2009). *The encyclopedia of positive psychology*. Wiley-Blackwell.

- Holmes, W., Bialik, M., & Fisher, D. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.
- Kukulska-Hulme, A., & Traxler, J. (2005). *Mobile learning: A handbook for educators and trainers*. Routledge.
- Leary, M. R., Tambor, E., Terdal, S., & Downs, D. L. (1995). Self-esteem as an interpersonal monitor: The sociometer hypothesis. *Journal of Personality and Social Psychology*, 68(3), 518–530.
- Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson.
- Mackinnon, N. J. (2015). *Self-esteem and beyond*. Palgrave Macmillan.
- Masrek, M. N., & Samadi, N. A. (2017). Assessing mobile learning readiness among students: A validation study. *International Journal of Interactive Mobile Technologies*, 11(1).
- Mouza, C., & Barrett-Greenly, T. (2015). Bridging the app gap: An examination of a professional development initiative on mobile learning in urban schools. *Computers & Education*, 88, 1–14. <https://doi.org/10.1016/j.compedu.2015.04.009>
- Naismith, L., Lonsdale, P., Vavoula, G., & Sharples, M. (2004). *Literature review in mobile technologies and learning (Futurelab Series Report 11)*. Futurelab.
- Narad, A., & Abdullah, B. (2016). Academic performance of senior secondary school students: Influence of parental encouragement and school environment. *Rupkatha Journal on Interdisciplinary Studies in Humanities*, 8(2), 12–19. <https://doi.org/10.21659/rupkatha.v8n2.02>
- Park, Y. (2011). A pedagogical framework for mobile learning: Categorizing educational applications of mobile technologies into four types. *International Review of Research in Open and Distance Learning*, 12(2), 78–102.
- Rosenberg, M. (1965). *Society and the adolescent self-image*. Princeton University Press.

- Schneider, M., & Preckel, F. (2017). Variables associated with achievement in higher education: A systematic review of meta-analyses. *Psychological Bulletin*, 143(6), 565–600. <https://doi.org/10.1037/bul0000098>
- Srivastava, L. (2005). Mobile Phones And The Evolution Of Social Behaviour. *Behaviour And Information Technology*, 24: p. 111-129. IJCATM : www.ijcaonline.org
- Stavropoulos, V., Lazaratou, H., Marini, E., & Dikeos, D. (2015). Low family satisfaction and depression in adolescence: The role of self-esteem. *Journal of Educational and Developmental Psychology*, 5(2), 109–118. <https://doi.org/10.5539/jedp.v5n2p109>
- UNESCO. (2012). *Turning on mobile learning: Global themes*. United Nations Educational, Scientific and Cultural Organization.
- VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist*, 46(4), 197–221. <https://doi.org/10.1080/00461520.2011.611369>
- Walsh, S. P., White, K. M., Cox, S., & Young, R. M. (2011). Keeping in constant touch: The predictors of young Australians' mobile phone involvement. *Computers in Human Behavior*, 27(1), 333–342. <https://doi.org/10.1016/j.chb.2010.08.011>